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Impact of Swiss intraday electricity market introduction on day-ahead prices and traded volume

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Declaration of Authorship

Authors hereby declare that they compiled this thesis independently, using only the listed resources and literature.

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Signature

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Contents

List of Tables **viii**

List of Figures **x**

Acronyms **xii**

1 Introduction **1**

2 A primer on electricity markets **3**
2.1 Wholesale electricity markets 3
2.2 The electricity market in Switzerland 5
2.3 Negative prices 8

3 Literature review **10**
3.1 Modeling electricity price performance 10
3.1.1 Modeling electricity price performance using realized variance measures 11
3.1.2 Modeling electricity price performance using GARCH . . . 12
3.2 Intraday electricity markets 13
3.3 Relationship between intraday and day-ahead electricity markets 14

4 Methodology **16**
4.1 Realized variance, bipower variation and estimation of jumps . . 17
4.2 Unequal variance t-test 21
4.3 GARCH 23

5 Data **26**

6 Empirical results **33**
6.1 Volatility of electricity prices on the day-ahead market 34
6.1.1 Realized variance measures and t-test 34

6.1.2 GARCH modeling 41
6.2 Volatility of traded volume of electricity on the day-ahead market 42
6.2.1 Realized variance measures and t-test 43
6.2.2 GARCH modeling 47
6.3 Traded volume of electricity on the day-ahead market 48
6.4 Discussion of results 50

7 Conclusion **54**

Bibliography **65**

A Volatility of electricity prices **I**

B Volatility of traded volume of electricity **VI**

List of Tables

5.1 Day-ahead volumes, prices and revenues: 1/1/2008–19/10/2016 28
5.2 Descriptive statistics of electricity prices: 28/3/13–25/6/13 and 27/6/13–24/9/13 28
5.3 Descriptive statistics of electricity volumes: 28/3/13–25/6/13 and 27/6/13–24/9/13 29
5.4 Descriptive statistics of the original price series, deseasonalised series and IHS-transformed deseasonalised series for: 3/3/10–19/10/16 30
5.5 Removing seasonality 31
5.6 Descriptive statistics of the original volume series, log series and demeaned log differences for: 3/3/10–19/10/16 32

6.1 Descriptive statistics of $r_{t,i}$, r_t, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity prices: 28/3/13–25/6/13 36
6.2 Descriptive statistics of $r_{t,i}$, r_t, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity prices: 27/6/13–24/9/13 37
6.3 Descriptive statistics of RV_t, C_t and J_t for electricity prices . . . 39
6.4 Relative jump contribution (J_t/RV_t) for electricity prices 40
6.5 Unequal variance t-test: Pre-intraday period vs. Post-intraday period (RV_t, C_t and J_t for electricity prices) 41
6.6 Unit root tests for IHS-transformed deseasonalised price series: 3/3/10–19/10/16 42
6.7 GARCH(1,1) model estimates with dummy variable for IHS-transformed deseasonalised price series: 3/3/10–19/10/16 42
6.8 Descriptive statistics of $r_{t,i}$, r_t, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity volumes: 28/3/13–25/6/13 44
6.9 Descriptive statistics of $r_{t,i}$, r_t, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity volumes: 27/6/13–24/9/13 45

6.10 Descriptive statistics of RV_t, C_t and J_t for electricity volumes . . 46
6.11 Relative jump contribution (J_t/RV_t) for electricity volumes . . . 47
6.12 Unequal variance t-test: Pre-intraday period vs. Post-intraday period (RV_t, C_t and J_t for electricity volumes) 47
6.13 GARCH(1,1) model estimates with dummy variable for demeaned log differences in volume series: 3/3/10–19/10/16 48
6.14 Descriptive statistics of demeaned differences of traded electricity volume: 28/3/13–25/6/13 and 27/6/13–24/9/13 49
6.15 Cramér-von Mises goodness-of-fit test: demeaned differences of traded electricity volume 49
6.16 Unequal variance t-test: Pre-intraday period vs. Post-intraday period (volumes) 50

A.1 Jarque–Bera ALM goodness-of-fit test for daily electricity price returns: 28/3/13–25/6/13 and 27/6/13–24/9/13 I
A.2 Cramér-von Mises goodness-of-fit test: RV_t, C_t and J_t (price volatility) I

B.1 Jarque–Bera ALM goodness-of-fit test for daily electricity volume changes: 28/3/13–25/6/13 and 27/6/13–24/9/13 VI
B.2 Cramér-von Mises goodness-of-fit test: RV_t, C_t and J_t (volume volatility) VI

List of Figures

2.1 EPEX SPOT in the market timeline 7

5.1 Hourly prices of electricity (EUR/MWh) on the Swiss day-ahead market: 1/1/08–19/10/16 27
5.2 Hourly volumes of electricity (MWh) on the Swiss day-ahead market: 1/1/08–19/10/16 27
5.3 Swissix Day Base Index (EUR/MWh): 3/3/10–19/10/16 29
5.4 Swissix Day Base Index (deseasonalised) (EUR/MWh): 3/3/10–19/10/16 31
5.5 EPEX SPOT Auction Market Volume (MWh): 3/3/10–19/10/16 . 32

6.1 Hourly price logarithmic returns on the Swiss day-ahead market: 1/1/08–19/10/16 35
6.2 Realized variance and variation components of electricity prices on the Swiss day-ahead market 38
6.3 Hourly price logarithmic changes on the Swiss day-ahead market: 1/1/08–19/10/16 43
6.4 Realized variance and variation components of electricity volumes on the Swiss day-ahead market 46

A.1 Quantile-quantile plot for daily price returns II
A.2 Histogram of standardized daily returns for electricity prices and standard normal probability density function III
A.3 Natural logarithm of RV_t for electricity prices IV
A.4 Jump component of RV_t (90^{th} perc.) for electricity prices V

B.1 Quantile-quantile plot for daily volume changes VII
B.2 Histogram of standardized daily returns for electricity volumes and standard normal probability density function VIII
B.3 Natural logarithm of RV_t for electricity volumes IX

B.4 Jump component of RV_t (90^{th} perc.) for electricity volumes . . . X

Acronyms

ADF Augmented Dickey-Fuller

ALM Adjusted Lagrange Multiplier

AR Autoregressive

ARCH Autoregressive Conditional Heteroskedasticity

ARMA Autoregressive moving average

BIC Bayesian information criterion

DF-GLS Dickey-Fuller Generalized Least Squares

ECC European Commodity Clearing

EEX European Energy Exchange

EGARCH Exponential Generalized Autoregressive Conditional Heteroskedasticity

EPEX SPOT European Power Exchange

GARCH Generalized Autoregressive Conditional Heteroskedasticity

IHS Inverse Hyperbolic Sine

OLS Ordinary Least Squares

PP Phillips-Perron

TGARCH Threshold Generalized Autoregressive Conditional Heteroskedasticity

TSO Transmission System Operator

VRES Variable Renewable Energy Sources

Chapter 1

Introduction

The Swiss energy market consists of two main markets: a day-ahead auction and a continuous intraday market. Both the day-ahead and intraday markets are operated by the EPEX SPOT which also operates the short-term electricity markets in Germany, France, the United Kingdom, the Netherlands, Belgium and Austria (EPEX SPOT SE 2016a).

Electricity supply from power stations and demand from consumers need to be balanced. High shares of electricity production from intermittent renewable energy sources make intraday electricity trading increasingly important as there is a need to efficiently balance these energy sources. The trend of increasing share of energy produced from renewable sources is also explicitly articulated in the Energy Strategy 2050 developed by the Swiss Federal Council. One of the key elements of this strategy is to increase the use of renewable energy and to stop building new nuclear power plants (Faust & Fetz 2014). Similarly, in Germany, "Energiewende" or energy transition can be mentioned. This is a policy of phasing out nuclear power and of increasing the share of renewable energy[1]. These developments in European countries are likely to substantially change the supply of electricity in Europe. According to Haas *et al.* (2013, p. 125), "renewables' contribution as a percentage of electricity generation within the EU will rise from 21% in 2010 to 34–36% by 2020".

The introduction of the electricity intraday market in Switzerland on June 26, 2013 provides an opportunity to evaluate the market performance outcomes if an intraday market is added to a day-ahead market since, as written by Scharff & Amelin (2016, p. 544), "intraday markets are still a research field with many open questions". Moreover, compared to the intraday electricity

[1]The target for the share of renewable energy sources in the energy supply is 60% by 2050 (World Nuclear Association 2016).

market launch in Germany, there have been written even fewer papers about the intraday electricity market launch in Switzerland. Also, as Ciarreta *et al.* (2017) stated recently: "There are not that many applications of realized volatility to electricity markets."

The volume of 15-minute contracts in Germany (intraday market launched in December 2011), Austria (intraday market launched in October 2012) and Switzerland altogether increased by approximately 69.3% from 4996.27 GWh in 2014 to 8459.52 GWh in 2016 and according to Kiesel & Paraschiv (2016, p. 1), this is partially explained by an increasing share of renewable energy "which requires power generators to balance out the forecasting errors in their production". Intraday markets allow market participants to decrease their expected imbalances and they can offer their unused capacity such that intraday deviations can be balanced from their day-ahead schedules through trading on the intraday markets.

We hypothesize that the introduction of an intraday market in Switzerland has resulted in a decrease in price volatility, volume volatility and traded volume on the day-ahead market. To test our hypotheses, we will perform t-tests for differences in volumes, price volatility and volume volatility on the day-ahead market before and after the launch of the intraday market. As a measure of volatility, we will use the realized volatility proposed by Andersen et al. (2001), which is defined as a sum of squared returns over a time interval. We will also decompose the total variance into its continuous and jump parts using realized variance and bipower variation and we will analyze the impact of the intraday market introduction on these components of volatility separately. In addition, we will estimate a GARCH model with a dummy variable to compare the level of (unconditional) price and volume volatility on the day-ahead market before and after the introduction of the intraday market.

Chapter 2

A primer on electricity markets

2.1 Wholesale electricity markets

Electricity spot markets are regulated by Power Exchanges or Independent System Operators. In day-ahead markets, participants submit bids for every hour of the following day. All collected bids are price-ordered and aggregated to create market demand and supply curves for each hour. The market is cleared by defining and announcing the equilibrium hourly price for the next day, which is determined by the intersection of the aggregated demand and supply curves.

After the day-ahead market closes on the day before delivery, trading continues on the day before delivery until shortly before physical delivery on the electronic intraday markets. These platforms allow market participants to self-balance unforeseen deviations from their day-ahead schedules. Because electricity can only be stored in limited amounts and it cannot be disposed of (Abrell 2016), electricity supply and demand must always be balanced. If there is an imbalance in the grid, control energy is needed. With a surplus supply of energy, negative control energy is withdrawn from the grid and the opposite applies in case of insufficient energy supply.[1]

Intraday markets are typically continuous and order driven markets. There are several different types of orders available to participants. One of them is a limit order, which carries a price limit (maximum bid price or minimum ask price)[2] determining if the order can be executed as limit orders can be executed only at that limit price or at a better price (asks are accepted at or above minimum ask price and bids are accepted at or below maximum

[1]For reference, on the Swiss national grid company Swissgrid, the share of requested control energy in total energy consumption was 1.11% in 2015 (Swissgrid Ltd 2016).

[2]Limit orders to sell are called asks and orders to buy are called bids.

bid price). The difference between the highest unmatched bid and the lowest unmatched ask is called the bid-ask spread (Neuhoff *et al.* 2016b). Other forms of orders are "iceberg" or hidden-quantity orders, market sweep orders and all-or-none orders. "Iceberg" orders are large orders divided into several smaller orders sequentially entered in the order book which defines the total set of orders at a given point in time and to which all market participants have access (Neuhoff *et al.* 2016b). Market sweep orders are user-defined block orders that are executed immediately and as far as possible against respective single-contract orders. All-or-none orders are executed completely or not at all.

The continuous intraday trading implements a pay-as-bid principle so market participants have to anticipate the clearing price and correspondingly mark up the bids they make in order to recover opportunity costs as all bids are cleared at the offer price. Optimal mark up depends on the equilibrium between demand and supply and thus should be continuously revised. In auctions, participants receive the market clearing/marginal price, i.e. the optimal trading strategy is to bid at marginal cost. Neuhoff *et al.* (2016a, p. 2) state that "power plant outages are more frequently resolved on a bilateral basis, than over the continuous market" as market participants retain part of their flexibility for a later new equilibrium between demand and supply. The market depth, i.e. the amount of electricity that is offered at certain prices at given times, is increased with introduction of intraday auctions (Neuhoff *et al.* 2016a; Hagemann & Weber 2015).

The energy industry in Europe is undergoing a rapid transformation, with variable renewable energy sources (VRES) becoming increasingly important and their share in total energy supply expected to increase significantly. This increases the necessity for intraday markets. As stated in EPEX SPOT SE (2015b, p. 10): "With the expansion of renewables depending on weather conditions it becomes more and more difficult to balance production and consumption." Haas *et al.* (2013) mention the following consequences of an increased share of renewables in the electricity generation:

1. Increased price volatility,
2. Increased importance of intraday markets,
3. Increased prices for fossil capacities and storage technologies to balance intermittent electricity generation from renewables,

4. Growth of balancing markets and increased competition among decentralized balancing organizations.

Consequently, intraday markets have been launched in the Czech Republic in 2004 (Rodryc *et al.* 2012), in Germany in 2006, in France in 2007 (European Commodity Clearing 2015) and in Austria in 2012 (EPEX SPOT SE 2016b).

2.2 The electricity market in Switzerland

The organised wholesale electricity market in Switzerland was launched in 2006. The owner and operator of the Swiss extra-high-voltage grid is the Swiss TSO, Swissgrid, which is responsible for the transmission of electricity. Due to the high initial investment costs, falling marginal costs and high irreversible costs, Swissgrid is a natural monopolist.

Switzerland is centrally located so it serves as a power hub for the European grid. Around 27.8 TWh of the flows on the Swiss transmission grid in 2015 have been caused by transit flows between two different countries: electricity exported from Germany to Italy travels via Switzerland and the same applies for the East-West axis. In 2015, Switzerland acted as a net exporter with 33.8 TWh exported and 33.5 TWh imported (Swissgrid Ltd 2016).

The value chain in the Swiss electricity industry can be divided as follows:

1. Electricity generation,
2. Electricity transmission,
3. Electricity distribution,
4. Electricity consumption.

The day-ahead auction takes place once a day, 365 days a year. The order book is opened 45 days before delivery and closes one day ahead of delivery – for Switzerland at 11:00. The publication time is as soon as possible from 11:10. The minimum price increment is 0.1 EUR/MWh and the minimum volume increment is 0.1 MWh. Prices have to be within a range from -500 to 3000 EUR/MWh. Information about trades is transmitted by EPEX SPOT to the ECC which is responsible for the clearing and settling of all products traded on EPEX SPOT. ECC submits its schedules to Swissgrid until 14:30 the day before delivery. Swissgrid then makes sure that these schedules match. The

price is determined each hour based on the equilibrium of supply and demand and all transactions are priced correspondingly (uniform pricing). According to EPEX SPOT SE (2015a, p. 1): "Hourly products on the day-ahead auction do not optimally fit balancing constraints, especially in the context of growing intermittent renewable feed-in", therefore "the more renewable energy will enter the system, the more short-term power trading will grow in the future" (EPEX SPOT SE 2015b, p. 10).

The intraday market in Switzerland was introduced on June 26, 2013 (El-Enien 2015). It provides flexibility and serves as a solution to the above-mentioned balancing issue as consumers and producers may be able to effectively balance their positions closer to real time with better forecasts. As stated by Borggrefe & Neuhoff (2011), the flexibility provided by the intraday market is especially beneficial in case of wind energy as uncertainty of wind forecasts decreases substantially in the last 24 hours before actual generation. Electricity on the Swiss intraday market is continuously traded 24 hours a day, every day of the year. Hourly contracts open at 15:00 on the day before delivery and 15-minute contracts open at 16:00. Prices have to be within a range from -9999 to 9999 EUR/MWh. Volume and price increments are the same as on the day-ahead market. On top of hourly, 30-minute[3] and 15-minute contracts, base (covering hours from 1:00 to 24:00) and peak (covering hours from 9:00 to 20:00 from Monday to Friday) contracts are traded. The advantages of intraday markets are summarized by EPEX SPOT SE (2013b):

1. Volumes that were not possible to trade on the auction can be bought or sold,

2. Last-minute portfolio optimization can be carried out (e.g. in case of an unplanned power plant outage),

3. Lower balancing costs due to better optimization possibilities and more efficient capacity usage,

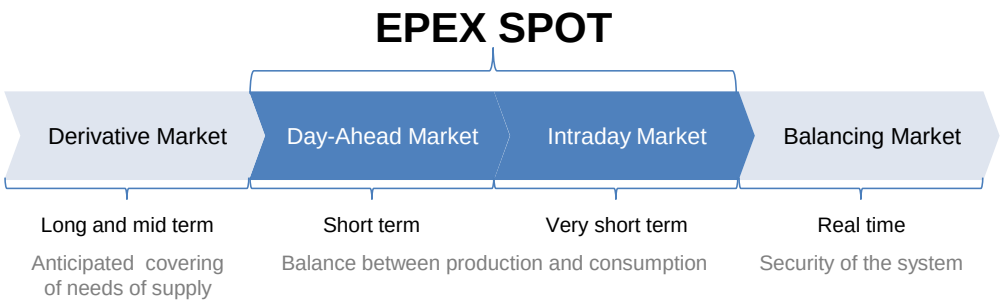
4. Possibility of arbitration between neighboring countries – opportunity for cross-border trading.

Based on the data from EPEX SPOT, we calculated that the average prices on the Swiss intraday market (EUR/MWh) in 2013 and 2014 were 49.46 and

[3]30-minute continuous trading of power spot contracts was introduced in the intraday markets in France, Germany and Switzerland on March 30, 2017.

42.66, respectively. Volumes in TWh for these two years were 0.98 and 2.31, respectively. Trading volumes are much higher in the day-ahead market than in the intraday market. Hence, the intraday market is of minor importance for trading and hedging but of higher importance for system security.

Figure 2.1: EPEX SPOT in the market timeline



Source: authors based on EPEX SPOT SE (2013c) .

Figure 2.1 presents how the day-ahead and intraday markets fit along the basic timeline of electricity trading activities. The long- and medium-term electricity production schedule is built in a derivative market, where futures and options are traded (Anhalt 2016). The production schedule is corrected in terms of hourly schedules of power plants on the day-ahead market, and positions are further adjusted on the intraday market. The derivative market is operated by The European Energy Exchange (EEX) which is, as EPEX SPOT, part of the EEX Group. 31 Swiss companies are currently trading on the EPEX SPOT markets and there are 75 market participants from all over Europe on the Swiss day-ahead market and 64 market participants on the Swiss intraday market.

The balancing market in Figure 2.1 is managed in Switzerland by Swissgrid and serves to guarantee the availability of power reserves necessary to secure the global equilibrium of supply and demand in real time, i.e. the time when demand and supply are known for certain. At real time supply and demand become known and they often diverge from their expected value, i.e. an imbalance occurs. Some generation capacity (reserve energy) has to be secured so that it is not contracted for energy sales and is therefore available. Historically, balancing markets have been the only markets providing power reserves and response operations.

Moving the gate closure, i.e. the point in time at which the market is

cleared, closer to real time increases flexibility, decreases anticipated imbalances between demand and supply and therefore increases the reliability of the system. However, gate closure cannot coincide with real time, because the TSO has to keep the transmission system stable by altering the generation and/or load pattern in order to change physical flows in the system (redispatching). It is worth pointing out that there is a difference between balancing and redispatching. Redispatching, the process of adjusting demand and supply schedules by the TSO, occurs before delivery time due to network problems when overloading of lines in the grid is expected. Usually, TSOs cannot use reserve capacity for redispatching.

To further increase liquidity on intraday markets, on October 5, 2016, the Dutch and Belgian intraday markets were connected with the intraday markets in Switzerland, Germany, France and Austria.

2.3 Negative prices

An interesting feature of electricity markets is the occurrence of negative prices. Since on wholesale markets electricity prices are driven by supply and demand, they fall with low demand. If low demand is met with highly inflexible power generation – from power sources that cannot be shut down and restarted in a quick and cost-efficient manner – prices can fall below zero. Negative prices are not a theoretical concept – sellers are actually providing electricity and paying the buyers because it is still cheaper for them to keep their power plants online than to shut them down and restart them later. Such situations arise mainly as a result of the large-scale renewable power generation, and the priority dispatch that the renewable support scheme provides them, forcing inflexible conventional power plants to ramp-down (Brandstätt *et al.* 2011). However, as Kyritsis *et al.* (2017, p. 553) describe: "renewables may stop generating electricity only a few hours later, and thereby base-load plants need to ramp-up quickly in order to serve the electricity demand. High opportunity costs may occur in these following hours, when prices are above variable costs for conventional power plants, due to their limited flexibility and expensive ramp-ups." It is worth mentioning that apart from these costs, long minimum standstill periods and accordingly revenue losses arise for the conventional power plants, before they can start producing again (Genoese *et al.* 2010). In fact, these long inactive periods threaten the sustainability of the conventional power plants

that need high utilization in order to cover their high investment costs (Nicolosi 2010).

The first occurrence of negative electricity prices on the EEX was in October 2008. Since then, they have become increasingly common events attracting considerable attention in the literature. Fanone *et al.* (2013) study the case of negative electricity prices in the German day-ahead spot market and emphasize their considerable challenge in energy risk management activities. In a similar study, Genoese *et al.* (2010) show that a sufficient condition for the appearance of negative prices is either a low system load, combined with a moderate wind generation or a moderate system load combined with high wind generation. Besides the other factors, they find wind generation to be the most important influential factor.

Chapter 3

Literature review

This chapter is divided into three sections. In the first section, we review the works about modeling and forecasting electricity prices. Next, we discuss separately studies that use realized volatility and GARCH for modeling electricity price performance. In the second section, we summarize selected papers about intraday electricity markets. In the last section of this chapter, we review papers about the relationship between intraday and day-ahead electricity markets.

3.1 Modeling electricity price performance

With the liberalization of power markets, electricity has become a tradable commodity. As a result, there has been a great deal of interest in understanding and modeling its price performance. Deng (2000), Huisman & Mahieu (2003), Lucia & Schwartz (2002) and Knittel & Roberts (2005) have been among the first to contribute to this research area and emphasize the distinct features of electricity prices. One important characteristic of electricity prices is seasonality. Demand for electricity can vary throughout the day, week and during the year. Knittel & Roberts (2005) and Lucia & Schwartz (2002) exemplify models of electricity price that incorporate seasonality. Another important characteristic is mean reversion. Since electricity is not storable, extreme prices that revert quickly may occur due to temporary imbalances in supply and demand. Therefore, Deng (2000) and Huisman & Mahieu (2003), among others, incorporate mean reversion in electricity price modeling.

An extensive body of literature exists on various modeling and forecast-

ing approaches for electricity spot prices. Fundamental modeling approaches are investigated by Pape *et al.* (2016), Weron (2014) and Janczura & Weron (2010). Mount *et al.* (2006) and Karakatsani & Bunn (2010) emphasise that variables for demand and available capacity should be included to better understand price movements. Huisman (2008) recognises that the price model can be improved when using temperature variables. Similarly, Hadsell (2006) and Gianfreda (2010) find that the trading volume has an effect on price volatility, which is in line with other studies on stock market movements, such as Bollerslev & Jubinski (1999) or Le & Zurbruegg (2010). Other modeling approaches are game theoretic models (Batlle & Barquín 2005; Ventosa *et al.* 2005), technical analysis and expert systems, econometric-stochastic models (Bowden & Payne 2008; Huisman & Mahieu 2003; Ketterer 2014; Kristiansen 2012; Nogales *et al.* 2002; Paraschiv *et al.* 2015) and artificial intelligence models (Cruz *et al.* 2011).

3.1.1 Modeling electricity price performance using realized variance measures

Chan *et al.* (2008) are to our knowledge the first authors to apply realized volatility to electricity data. They separate the total variation into its jump and continuous components, as we do later in the thesis. Specifically, they use spot prices from five power markets operating in different regions in Australia for the analysis. They find that jumps make a disproportionate contribution to the total variation (up to 11% of the total variation and it varies based on the physical nature of the electricity generation in the corresponding market). The authors also find that the mean jump sizes are considerably higher compared to the results in papers employing parametric methods to model volatility.

Haugom *et al.* (2011) were the first to use high-frequency data and evaluate the concept of realized volatility in the Nord Pool electricity forward market. They also separate the total variation into its two components and add exogenous effects (e.g. total trading volume, time to delivery etc.) which, as found, improve significantly the volatility predictions compared to the model used by Chan *et al.* (2008). The authors also find that the decomposition into jump and continuous components results in the case of both quarterly and yearly contract series in more precise day-ahead forecasts compared to the Heterogenous Autoregressive Model of Realized Volatility.

Ciarreta & Zarraga (2016) model realized volatility of the hourly prices on

the Spanish intraday electricity market for a period between 2002 and 2014. The authors decompose the total volatility in its continuous and jump parts by comparing two measures of variance (realized variance and bipower variation) and test the statistical significance of the difference between these two measures. This paper is closely related to Ullrich (2012), who calculates the realized volatility and estimates the frequency of price spikes for eight wholesale electricity markets.[1] This study demonstrates that jump detection techniques developed for use in financial markets must be modified for use in electricity markets. Jumps in high frequency electricity prices are inevitably followed by reversals that induce negative serial correlation in returns, which causes the jump detection statistic to underreject the null of no jumps. Therefore, the author shows that in order to account for reversals it is crucial to increase the lag length by several periods.

Qu *et al.* (2016) also apply realized volatility to model and forecast jump and continuous volatility in electricity prices from the Australian New South Wales electricity market. The authors also propose a group of logistic smooth transition heterogeneous autoregressive models of realized volatility which can at the same time approximate long memory behavior and describe size and sign asymmetries. The results indicate that introducing the logistic smooth transition structure to the Heterogenous Autoregressive Models is beneficial.

3.1.2 Modeling electricity price performance using GARCH

Given the pronounced volatility in electricity markets, the GARCH family of models is very well suited to correctly explain price performance in these markets (Higgs & Worthington 2010). GARCH models, which date back to Bollerslev (1986), are widely used in financial and commodity markets because they appropriately capture the fluctuation and clustering of volatility. Knittel & Roberts (2005) were amongst the first to apply a GARCH model to electricity prices. They employ an asymmetric GARCH model to capture price responses to positive and negative shocks and detect an inverse leverage effect, i.e. positive shocks to the price series result in larger increases in volatility than negative shocks. The volatility of wholesale electricity spot markets for five European markets[2] is analyzed by Gianfreda (2010), who documents volatility clustering, persistence and asymmetric effects, using GARCH models after filtering outliers.

[1] Five in Australia, one in Canada and two in the U.S.

[2] The volatility of French, Spanish, German, Dutch and Italian electricity wholesale prices is analyzed.

Seasonality is also identified as an important feature that affects volatility dynamics.

Other GARCH applications include Solibakke (2002), who applies a BIC efficient ARMA-GARCH lag specification to model the electricity price dynamics in the Nordic Spot electric power market, and Mugele *et al.* (2005), who use ARMA-GARCH time series models with Gaussian and stable innovations for modeling the behavior of electricity prices on the German, Nordic and Polish power markets. Furthermore, Escribano *et al.* (2011) contribute to the literature by combining jumps and GARCH to explicitly control for price spikes. They show that taking into account mean reversion, seasonality and jumps improve the GARCH model.

Ciarreta & Zarraga (2015) analyze the degree of integration between electricity spot markets in Spain, Portugal, Austria, Germany, Switzerland and France, using multivariate GARCH models to study the mean and volatility spillovers within these markets. They find evidence of dynamic conditional correlation between Spain and Portugal, Germany and Austria, and Switzerland and Austria, but not for the Spain-France and Germany-France pairs, with significant mean and volatility spillovers in the rest of the country pairs.

Kyritsis *et al.* (2017) use univariate GARCH-in-Mean models to investigate the effects of intermittent solar and wind generation on electricity price formation in Germany. They find that solar power generation reduces the probability of electricity price spikes as well as the volatility of electricity prices. Conversely, wind power generation was found to introduce electricity price spikes and increase price volatility. In a closely related study, Ketterer (2014) also investigates the relationship between intermittent wind power and electricity price behavior in Germany. This paper's results show that intermittent wind power generation decreases the wholesale electricity price but increases its volatility. Additionally, this study explores the impact of a 2010 regulatory change to the marketing mechanism of renewable electricity and finds that price volatility has decreased after the change.

3.2 Intraday electricity markets

Kiesel & Paraschiv (2016) analyze the bidding behavior in the intraday electricity market and they model intraday prices based on the latest forecasts for wind and photovoltaic energy available to market participants before they place their

price bids.[3] The authors propose a forecasting model for the changes between last prices bid intraday for a particular 15-minute period and the corresponding day-ahead price. They also derive a fundamental model for the price changes in the continuous bidding and they find that there is an impact of forecasting errors in renewables on bidding behavior: with negative forecasting errors, intraday prices increase and vice versa for positive forecasting errors.

Scharff & Amelin (2016) analyze the trading activity and price development on the European intraday market Elbas. Despite Elbas being a continuous intraday trading platform, authors find that most trades occur in the last hours before gate closure and that trading activity differs to a large extent across price zones.

Several countries in Europe such as Italy, Spain and Germany launched auction-based intraday markets. Neuhoff *et al.* (2016b) study whether the addition of intraday auctions to the continuous intraday trading leads to an improvement in market performance. The authors focus on the German market where a 15-minute intraday auction was introduced in December 2014. The authors find that intraday auctions are particularly advantageous for small market players who are not equipped for continuous trading. Generally, they find that the addition of intraday auctions increases liquidity, reduces price volatility and leads to a higher market depth defined as the amount of electricity that is offered at certain prices at given times.[4] These results are consistent with Hagemann & Weber (2015), who already found that liquidity in the countries of Central Western Europe is lower compared to Spain and Italy, where intraday auction trading is present.

3.3 Relationship between intraday and day-ahead electricity markets

Weber (2010) reviews the market designs of the major European power markets in France, Germany, Scandinavia, Spain and UK, focusing on the liquidity in the day-ahead and intraday markets. The author highlights the importance

[3]The authors state that "market participants have private access to the freshest weather forecasts for a certain quarter of an hour (delivery period) and use this information for adjusting their bids accordingly" (Kiesel & Paraschiv 2016, p. 13).

[4]As stated by Neuhoff *et al.* (2016b, p. 6), "the higher the market depth, the more of the available flexibility is directly offered to the market, and, therefore, the more likely it is that synergies across the system can be realized".

of an efficiently functioning intraday market for addressing short-term deviations between day-ahead plans and actual delivery and lays out alternatives to improve the functioning of the intraday markets within existing market designs.

Hagemann (2013) studies the determinants of hourly prices on the German intraday electricity market and identifies the price difference between the German day-ahead and intraday markets. Similarly to the analysis by Kiesel & Paraschiv (2016), this study shows that forecasting errors (specifically wind and solar forecast errors) significantly influence intraday prices. The author also finds that intraday prices tend to be lower (higher) when the day-ahead prices are above 55 EUR (below 35 EUR).

Furio *et al.* (2009) analyze the price convergence between the Spanish day-ahead and intraday markets from 2000 to 2005 and find significant price differences between both markets.

Chaves-Avila & Fernandes (2015) use day-ahead and intraday market prices and also intraday trading volumes to examine the behavior of market participants in the Spanish intraday market. They also analyze the impact of support schemes regarding renewable generators on the intraday market participants' behavior. The authors find that the intraday market helps balancing renewable generation, however some renewable energy generators tend to take an advantage of market distortions by arbitrating between the day-ahead and intraday market. This leads to an increase in system costs as such behavior has an impact on the need for balancing reserves.[5]

[5]According to OECD Nuclear Energy Agency (2012), system costs are defined as "the total costs accrued beyond the perimeter of a power plant to supply electricity at a given load and at a given level of security of supply" and they are higher for renewables than for nuclear, coal and gas, because of the "variability and unpredictability of renewable output. This increases the costs associated with balancing short-term supply and demand variations and ensuring the long-term adequacy of electricity supply, which are two major components of the costs of running an electricity system." Moreover, the production of renewable energy is usually placed further from the location of demand and from the existing transmission grid.

Chapter 4

Methodology

In the first approach, we identify comparable time periods before and after the introduction of the intraday market and perform t-tests for differences in volumes, price volatility and volume volatility on the day-ahead market. As a measure of volatility, we use the realized volatility proposed by Andersen *et al.* (2011). We also decompose the total variance into its continuous and jump parts using realized variance and bipower variation and again test for differences between periods before and after the intraday market introduction using the unequal variance t-test.

In the second approach, we estimate a GARCH model with a dummy variable to compare the level of (unconditional) volatility on the day-ahead market before and after the introduction of the intraday market. The impact of the intraday market introduction is tested by amending the conditional variance equation of the GARCH model with a dummy variable which takes values 0 for the pre-intraday period, and 1 for the post-intraday period.

Zheng *et al.* (2014), among others, divides the methods of calculating volatility into two groups: parametric and nonparametric. Parametric techniques, such as the GARCH model described in this chapter, assume a specific functional form for the expected and/or instantaneous volatility. On the other hand, nonparametric methods, such as the realized variance described below, do not assume any explicit functional form (Andersen *et al.* 2010a).

4.1 Realized variance, bipower variation and estimation of jumps

Similarly to Ciarreta & Zarraga (2016), who model the realized volatility of the hourly prices from the Spanish intraday market, we model the realized variance of hourly prices and volumes from the Swiss day-ahead market and decompose it into its continuous and jump parts. Realized variance focuses on the volatility measured ex-post so it can be calculated without any link to a specific model.

Let us consider a univariate logarithmic price process, $p_t = \ln P_t$, where P_t is the price process on day t. Similarly, let us consider a univariate logarithmic volume process, $v_t = \ln V_t$, where V_t is the volume process on day t. Consider the following continuous-time jump-diffusion process for $p_t = \ln P_t$ (and analogically for $v_t = \ln V_t$)

$$\mathrm{d}p_t = \mu_t \mathrm{d}t + \sigma_t \mathrm{d}W_t + \xi_t \mathrm{d}q_t, \tag{4.1}$$

where μ_t is the drift term (predictable, finite-variation component), $\sigma_t > 0$ is the spot (point-in-time) volatility process (measure of the standard deviation of the returns) assumed to be càdlàg[1], W_t is a standard Brownian motion, q_t is a jump indicator ($q_t = 1$ if there is a jump at time t and 0 otherwise) and ξ_t corresponds to the magnitude of the jump (if any occurs at time t).

Our dataset contains negative prices, which prevents us from making a logarithmic transformation. Since we prefer not to ignore negative prices in our analysis, we chose to apply the IHS transformation to all prices as $\ln\left[P + \sqrt{P^2 + 1}\right]$. This transformation preserves the behavior of the logarithmic transformation for positive prices with the advantage that it is also defined for nonpositive prices.[2] The IHS transformation has been widely used in wealth studies, but examples of its use for modeling negative power prices can be found in Schneider (2012) and Ciarreta & Zarraga (2015). We do not apply the IHS transformation in the volume change calculation as can be seen in Equation 4.3.

Let $p_{t,i}$ be the ith logarithmic price on day t. Then, we define the ith intraperiod price return on day t as

[1]The càdlàg function is a right continuous function which has left limits at each point.

[2]The IHS transformation assumes that the behavior of negative prices is a symmetric reflection of the behavior of the positive ones.

$$r_{t,i} = \ln\left(P_{t,i} + \sqrt{P_{t,i}^2 + 1}\right) - \ln\left(P_{t,i-1} + \sqrt{P_{t,i-1}^2 + 1}\right) = p_{t,i} - p_{t,i-1}. \quad (4.2)$$

The difference in time between observing $p_{t,i}$ and $p_{t,i-1}$ corresponds to the sampling frequency which in our case is equal to one hour.

We define volume changes similarly as price returns, but without the IHS transformation, i.e. simply as a difference in natural logarithms of consecutive volumes. Let $v_{t,i}$ be the ith logarithmic volume on day t. Then, the ith intraperiod volume change of day t is calculated as

$$r_{t,i}^v = \ln\left(\frac{V_{t,i}}{V_{t,i-1}}\right) = \ln\left(V_{t,i}\right) - \ln\left(V_{t,i-1}\right) = v_{t,i} - v_{t,i-1}. \quad (4.3)$$

The realized variance of electricity prices is defined as the sum of all intraday squared price returns

$$RV_t = \sum_{i=1}^{n} r_{t,i}^2, \quad (4.4)$$

where n denotes the total number of return observations per day. The realized variance of electricity volumes is defined analogically.

As mentioned by Ullrich (2012), electricity prices do not behave in the same way as stock prices do. Electricity prices vary based on the hour within a day, the day within a week and the month within a year. For example, prices tend to be higher during peak hours, weekdays and winter periods (Ciarreta & Zarraga 2016). Therefore, adjustments for seasonality and peak and off-peak hours need to be made when calculating the volatility. Following Ullrich (2012) and Ciarreta & Zarraga (2016), we subtract from each observation the median of price difference for day t during each month, day within a week and hour. As stated by DG Energy (2014, p. 4): "There is a strong seasonality in electricity consumption at EU level, as during the winter period lighting and heating needs result in higher demand for power." Therefore, we also adjust for seasonality. Specifically, $r_{t,i}$ in Equation 4.4 is replaced in the case of both realized variance of prices and realized variance of volumes by

$$r_{t,i}^* = r_{t,i} - \widehat{\mu_{t,i}}, \quad (4.5)$$

where $\widehat{\mu_{t,i}} = r_{mn,dy,hr}$ is the median return for day t in month mn, on weekday dy, and hour $i = hr$. However, in the following chapters when analyzing the volatility of prices and volumes, we denote both price returns and volume

changes as $r_{t,i}$. They will be analyzed separately to avoid any confusion. The adjustment for seasonality is done in a similar way for volume levels as

$$V_d^* = V_d - \widehat{\nu_{t,i}}, \tag{4.6}$$

where V_d is the change in volume for day t and hour i, and $\widehat{\nu_{t,i}} = d_{mn,dy,hr}$ is the median change in volume for day t in month mn, on weekday dy, and hour $i = hr$.

We also define realized volatility as the square root of realized variance, i.e.

$$RVO_t = \sqrt{RV_t}. \tag{4.7}$$

In order to decompose the total variation into its continuous and jump components, we need to define the realized bipower variation. Ullrich (2012, p. 1812) states that "a large upward movement in electricity prices inevitably is followed shortly thereafter by a reversal, or a return to the normal price level". Therefore, when jumps are present, the following returns demonstrate negative serial correlation. This autocorrelation is stemming from different sources than the microstructure noise in the case of equity returns.[3] However, as mentioned by Ullrich (2012), the effect is the same. Generally, it makes the realized bipower varation larger compared to the case of no reversals, causing the difference $RV_t - RBV_t$ and therefore also the Z_t statistic defined in Equation 4.14 to be smaller. Consequently, the test would tend to underreject the null hypothesis of no within-day jumps.

As found by Andersen *et al.* (2007), the serial correlation can be broken by using "staggered, or skip-one, returns". Therefore, we follow the definition given by Andersen *et al.* (2011) and we define the realized bipower variation as

$$RBV_t = \mu_1^{-2} \frac{n}{n-2} \sum_{i=3}^{n} |r_{t,i-2}||r_{t,i}|, \tag{4.8}$$

where $\mu_r = E\left(|Z|^r\right) = 2^{r/2} \frac{\Gamma((r+1)/2)}{\Gamma(1/2)}$ for $r > 0$, $Z \sim N(0,1)$ and $\Gamma(\cdot)$ denotes the Gamma function. In our case, $\mu_1 = \sqrt{2/\pi}$.

The realized variance is the estimator of quadratic variation which is a

[3]Microstructure noise can be caused by bid-ask bounce, i.e. the situation when the trade price oscillates between the bid and ask side of the market, asynchronous (nonsynchronous) trading, that is when the underlying return process is observed at irregular intervals (the trading intensity can thus vary) and discreteness of prices, among others.

measure of the volatility on day t and is defined as

$$QV_t = \int_{t-1}^{t} \sigma_s^2 \, \mathrm{d}s + \sum_{t-1<s\leq t} J_s^2, \tag{4.9}$$

where the first term on the right-hand side is the (continuous) integrated variance and the second term is the contribution to overall variation caused by the presence of jumps. Therefore, in the case that jumps are not present, the quadratic variation equals the integrated variance defined as

$$IV_t = \int_{t-1}^{t} \sigma_s^2 \, \mathrm{d}s. \tag{4.10}$$

The bipower variation converges in probability to the integrated variance with the total number of return observations per day increasing to infinity as mentioned by Andersen *et al.* (2010b) and Huang & Tauchen (2005), among others. This means that

$$\mathrm{plim}_{n\to\infty} \, RBV_t = IV_t. \tag{4.11}$$

As also mentioned by Andersen *et al.* (2010b) and Huang & Tauchen (2005), the realized variance converges uniformly in probability to the quadratic variation, i.e.

$$\mathrm{plim}_{n\to\infty} \, RV_t = QV_t. \tag{4.12}$$

Therefore, we get a consistent estimator of jumps by differencing RV_t and RBV_t, i.e.

$$\mathrm{plim}_{n\to\infty} \left(RV_t - RBV_t\right) = \sum_{i=1}^{m_t} J_{t,i}^2, \tag{4.13}$$

where m_t denotes the number of jumps over day t.

Based on Andersen *et al.* (2011), the following test statistic is used for detecting the presence of jumps:

$$Z_t = \frac{\frac{RV_t - RBV_t}{RV_t}}{\sqrt{\frac{1}{n}\left(\left(\frac{\pi}{2}\right)^2 + \pi - 5\right) \cdot \max\left(1, \frac{RTQ_t}{RBV_t^2}\right)}}, \tag{4.14}$$

where RTQ_t is the realized tripower quarticity defined as

$$RTQ_t = n\mu_{4/3}^{-3}\left(\frac{n}{n-4}\right)\sum_{i=5}^{n}|r_{t,i-4}|^{4/3}|r_{t,i-2}|^{4/3}|r_{t,i}|^{4/3}, \tag{4.15}$$

where $\mu_{4/3} = 2^{2/3}\frac{\Gamma(7/6)}{\Gamma(1/2)}$.

Z_t in Equation 4.14 has an asymptotically standard normal distribution under the null hypothesis of no within-day jumps and under sufficient regularity conditions (Andersen *et al.* 2011).

Following Andersen *et al.* (2011), the realized measure of the jump contribution to the quadratic variation of the logarithmic process is defined as

$$J_t = I(Z_t > \Phi_\alpha)(RV_t - RBV_t), \tag{4.16}$$

where Φ_α is a critical value from the $N(0,1)$ distribution[4] and $I(\cdot)$ is the indicator function[5].

The realized measure of the integrated variance is then defined as follows

$$C_t = I(Z_t \leq \Phi_\alpha)\cdot RV_t + I(Z_t > \Phi_\alpha)\cdot RBV_t. \tag{4.17}$$

Therefore, if no within-day jumps are detected, the continuous component is estimated by realized variance. Otherwise, it is estimated by realized bipower variation, i.e. the continuous and jump components always add up to the daily realized variance.

4.2 Unequal variance t-test

According to Ruxton (2006), experimenters should decide which t-test to use (either the t-test with equal variances or the unequal variance t-test known as Welch's t-test[6]) and ignore the other one. The author states that even in a case when the population variances are equal, Welch's t-test's power is similar to the power of the Student's t-test assuming the equality of variances as written above. Ruxton (2006, p. 689) also recommends "avoiding preliminary tests

[4]The 95$^{\text{th}}$ percentile of the standard normal distribution is used in this thesis.

[5]I(*statement*) denotes an indicator function that equals 1 if the *statement* is true and 0 if it is false.

[6]It is a Welch's approximation for the degrees of freedom (referred to as the Welch Approximate Degrees of Freedom), which calculates the degrees of freedom from the two samples sizes differently from the Student's t-test as shown in the text.

and adopting the unequal variance t-test unless an argument based on logical, physical, or biological grounds can be made as to why the variances are very likely to be identical". The problem with firstly performing a preliminary test for equality of variances and subsequently any of the two mentioned t-tests is that an experimenter would decide whether to perform one statistical test based on the outcome of another test, controlling Type I error rates worse than performing directly the Welch's t-test in every situation. Therefore, we define and subsequently use only the unequal variance t-test.

If μ_{i_1} is the true population mean of the realized variance (or its components) of electricity prices (RV_P), the variance (or its components) of traded volume of electricity (RV_V) or the traded volume of electricity (V_d) on the day-ahead market in Switzerland before the introduction of the intraday market and μ_{i_2} is the true population mean of RV_P, RV_V or V_d after the introduction, then the null hypothesis in our t-test is

$$H_0 : \mu_{i_1} - \mu_{i_2} \leq 0 \tag{4.18}$$

where $i = \{RV_P,\ RV_V,\ V_d\}$ and the alternative hypothesis is that the mean difference is greater than zero

$$H_A : \mu_{i_1} - \mu_{i_2} > 0. \tag{4.19}$$

Let $\bar{X}_{i_1}$ be the sample mean of RV_P, RV_V or V_d before introduction of the intraday market in Switzerland and $\bar{X}_{i_2}$ be the sample mean of RV_P, RV_V or V_d after the introduction. Let $s_{i_1}^2$ and $s_{i_2}^2$ be the respective variances and n_{i_1} and n_{i_2} be the corresponding sample sizes. According to the definition by Ruxton (2006), the unequal variance t-test statistic is

$$t = \frac{\bar{X}_{i_1} - \bar{X}_{i_2}}{\sqrt{\frac{s_{i_1}^2}{n_{i_1}} + \frac{s_{i_2}^2}{n_{i_2}}}}. \tag{4.20}$$

As can be seen, the variances of the two samples are not pooled as is the case in the Student's t-test. The Welch's t-test is performed at the 0.05 significance level in this thesis. The number of degrees of freedom is calculated as

$$\nu = \frac{\left(\frac{1}{n_{i_1}} + \frac{u}{n_{i_2}}\right)^2}{\sqrt{\frac{1}{n_{i_1}^2 \cdot \left(n_{i_1} - 1\right)} + \frac{u^2}{n_{i_2}^2 \cdot \left(n_{i_2} - 1\right)}}}, \tag{4.21}$$

where

$$u = \frac{s_{i_2}^2}{s_{i_1}^2}. \tag{4.22}$$

4.3 GARCH

The GARCH modeling approach we adopt is common for financial time series, and has been applied to electricity prices in previous literature. Following Ketterer (2014), Kyritsis *et al.* (2017) and Chevallier *et al.* (2011), among others, we use the logarithms of daily day-ahead electricity prices (daily day-ahead traded volumes), $p_{t,i}$ ($v_{t,i}$), as the dependent variable in a GARCH estimation.[7] Our goal is to model directly the heteroscedasticity in the variance of a price series (volume series), hence the choice of the dependent variable in the GARCH analysis.

We utilize the GARCH family of statistical models to investigate the volatility of electricity prices and traded volume on the day-ahead market both before and after the introduction of the intraday market. GARCH models are well suited to the study of volatility since they account specifically for systematic changes in the variance of a time series by modeling the conditional variance. GARCH models also allow us to take into account volatility clustering, indicated by fat-tails in the distribution of financial time series.

The autoregressive conditional heteroscedastic (ARCH) model was first proposed by Engle (1982). Unlike traditional regression techniques where the error term is assumed to be homoscedastic, the ARCH model allows the error variance to change over time as a linear function of lagged squared errors. For instance, an AR(1) process with errors that follow an ARCH(q) process would be represented as follows

$$X_t = \beta_0 + \beta_1 X_{t-1} + \epsilon_t, \tag{4.23}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2, \tag{4.24}$$

where $\epsilon_t \sim N(0, h_t)$.

Bollerslev (1986) extended Engle's ARCH to a generalized ARCH, or GARCH

[7] Although we transform the original price and volume series to correct for outliers, seasonality, etc. as described in the following chapter

process. Unlike the ARCH(q) process where the conditional variance is specified as a linear function of past sample variances only, the GARCH(p,q) process allows lagged conditional variances to enter as well, which is similar to a kind of adaptive learning mechanism. A GARCH(p,q) process is represented as

$$\epsilon_t|\psi_{t-1} \sim N(0, h_t), \tag{4.25}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} = \alpha_0 + A(L)\epsilon_t^2 + B(L)h_t, \tag{4.26}$$

where $p \geq 0$, $q > 0$, $\alpha_0 > 0$, $\alpha_i \geq 0$, $i = 1, ..., q$, $\beta_i \geq 0$, and $i = 1, ..., p$. For $p = 0$ the process reduces to the ARCH(q) process, and for $p = q = 0$, ϵ_t is simply white noise. The GARCH(p,q) regression model is obtained by letting the ϵ_t's be innovations in a linear regression

$$\epsilon_t = y_t - x_t' b, \tag{4.27}$$

where y_t is the dependent variable, x_t a vector of explanatory variables and b a vector of unknown parameters.

The impact of the introduction of the intraday market is tested by amending the conditional variance equation of the GARCH model with a dummy variable which takes the value of 0 for the pre-intraday period, and the value of 1 for the post-intraday period. This methodology has been applied by Antoniou & Holmes (1995) and Gulen & Mayhew (2000) for financial markets, Antoniou & Foster (1992) for the crude oil market and Chevallier *et al.* (2011) for the European Union Emissions Trading Scheme. Then, we adopt the structure of a GARCH(1,1) model

$$p_t = \beta_0 + \epsilon_t, \tag{4.28}$$

where $\epsilon_t \sim \sqrt{h_t} e_t$ with $e_t \sim iid(0, 1)$ and

$$h_t = E(\epsilon_t^2|\phi_{t-1}) = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1} + \gamma DF_t \tag{4.29}$$

with p_t being the daily electricity price (v_t for daily volumes), ϕ_{t-1} being the set of past information and ϵ_t being the error term. In the conditional variance in Equation 4.29, DF_t is a dummy variable taking the value of 0 before the introduction of the intraday market, and 1 thereafter. This dummy variable

allows to test for the influence of the introduction of the intraday market on the volatility of the electricity prices and traded volume on the day-ahead market.[8]

[8]The dummy variable in the volatility equation of a GARCH model has an effect on the unconditional level of volatility as it is invariant through time.

Chapter 5

Data

Hourly prices and traded volumes on the Swiss day-ahead market are considered for the period from January 1, 2008 to October 19, 2016. As we have 24 observations per day and the period consists of 3215 days, we have 77,160 observations in total[1]. Prices are measured in EUR/MWh and they are obtained from the EPEX SPOT.

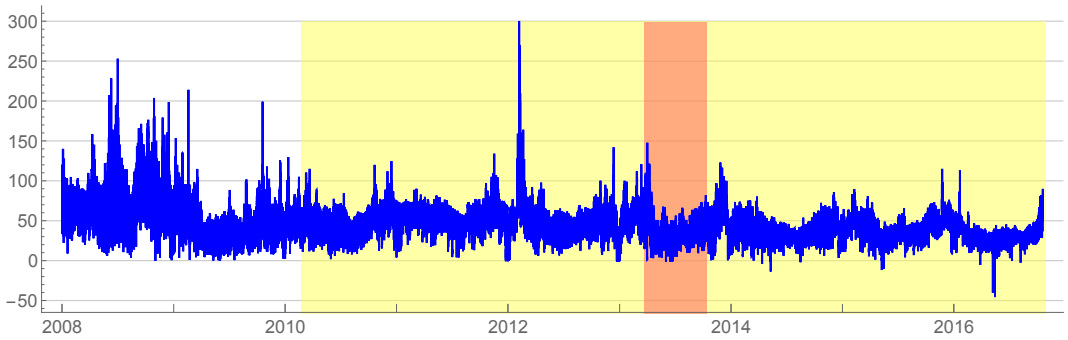
In Figure 5.1, we present the development of hourly prices of electricity on the Swiss day-ahead market in the period from January 1, 2008 to October 19, 2016. The highest price was on February 7, 2012 and was equal to 300.04 EUR/MWh (9:00–10:00). Based on DG Energy (2012), a severe cold spell in the first two weeks of February 2012 impacted almost all Europe. This resulted in year highs of wholesale electricity prices in most of the European markets. The minimum price was observed on May 15, 2016 and was equal to -45.68 EUR/MWh (15:00–16:00). There were 48 negative prices during the period from January 1, 2008 to October 19, 2016 and the two days with the largest number of negative prices within a day were May 15, 2016 (15 out of 24 prices were negative) and May 11, 2014 (7 negative prices during that day).

In Figure 5.2, we present the development of the hourly electricity volumes on the Swiss day-ahead market in the period from January 1, 2008 to October 19, 2016. The highest traded volume of electricity was on May 22, 2015 and was equal to 5676.7 MWh (6:00–7:00).

In Table 5.1, we provide a summary of volumes, prices and revenues on the day-ahead market from January 1, 2008 to October 19, 2016. We can see that

[1]Seven observations within the period from January 1, 2008 to October 19, 2016 are missing for electricity prices and volumes so we have 77,153 data points in total for each series. As the missing observations consist of only an insignificant portion of the whole dataset, we do not expect that our analysis will be influenced by that. Moreover, not all of the missing observations fall within the analyzed period.

Figure 5.1: Hourly prices of electricity (EUR/MWh) on the Swiss day-ahead market: 1/1/08–19/10/16

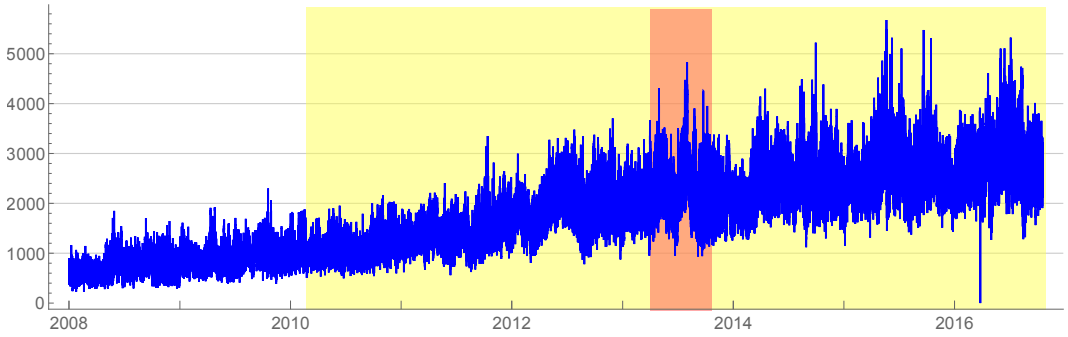


This figure presents the development of the electricity prices on the Swiss day-ahead market from January 1, 2008 to October 19, 2016. For the first approach, we use data from March 28, 2013 to June 25, 2013 and from June 27, 2013 to September 24, 2013 (indicated by red background; including June 26, 2013). For the second approach, we use data from March 3, 2010 to October 19, 2016 (indicated by yellow background).

Source: authors and data from the EPEX SPOT.

volumes have been continuously increasing since 2008. However, the prices on the day-ahead market have been rather volatile within this period with the highest average price of 75.86 in 2008.

Figure 5.2: Hourly volumes of electricity (MWh) on the Swiss day-ahead market: 1/1/08–19/10/16



This figure presents the development of the electricity volumes on the Swiss day-ahead market from January 1, 2008 to October 19, 2016. For the first approach, we use data from March 28, 2013 to June 25, 2013 and from June 27, 2013 to September 24, 2013 (indicated by red background; including June 26, 2013). For the second approach, we use data from March 3, 2010 to October 19, 2016 (indicated by yellow background).

Source: authors and data from the EPEX SPOT.

Table 5.2 presents the descriptive statistics of the data used in the analysis of the volatility of prices based on realized variance measures and t-tests. The

Table 5.1: Day-ahead volumes, prices and revenues: 1/1/2008–19/10/2016

	Volume [TWh]	Avg. Price [EUR/MWh]	Base Price [EUR/MWh]	Peak Price [EUR/MWh]	Revenues [Million EUR]
2008	6.16	75.86	74.38	88.57	466.98
2009	8.01	47.97	47.92	56.93	384.13
2010	9.32	51.64	51.02	57.82	481.55
2011	12.06	57.01	56.18	61.76	687.64
2012	16.68	49.43	49.52	55.65	824.45
2013	18.74	44.82	44.73	49.98	839.98
2014	20.47	36.67	36.79	40.62	750.47
2015	22.91	40.29	40.29	43.38	923.20
2016	19.41	32.51	32.43	34.77	630.87

This table summarizes volumes, prices and revenues on the day-ahead market from January 1, 2008 to October 19, 2016. Average prices are calculated as weighted average using traded volumes as weights. For base and peak prices the unweighted mean is reported. 2016 numbers are based on data up to October 19.

sample is based on 2159 (pre-intraday market period) and 2160 (post-intraday market period) price observations.

Table 5.2: Descriptive statistics of electricity prices: 28/3/13–25/6/13 and 27/6/13–24/9/13

	Pre-intraday period	Post-intraday period
Mean	36.575	38.296
Std. dev.	20.035	12.801
Min	0	4.71
Max	147.71	67.88
Skewness	0.930	0.057
Kurtosis	4.863	2.256
Obs.	2159	2160

This table presents the descriptive statistics of the data used for the price volatility analysis based on realized variance measures and t-tests.

Similarly, we present in Table 5.3 the descriptive statistics of the data used in the volume volatility and volume level analysis using the first approach. As in the above case, we have 2159 and 2160 data points.

For GARCH modeling, we use daily Swiss electricity spot prices over the period from March 3, 2010 to October 19, 2016, i.e. a total of 2423 observations. Specifically, we use the day-ahead spot electricity price, Swissix Day Base, which is calculated as the arithmetic mean of the market clearing prices of the

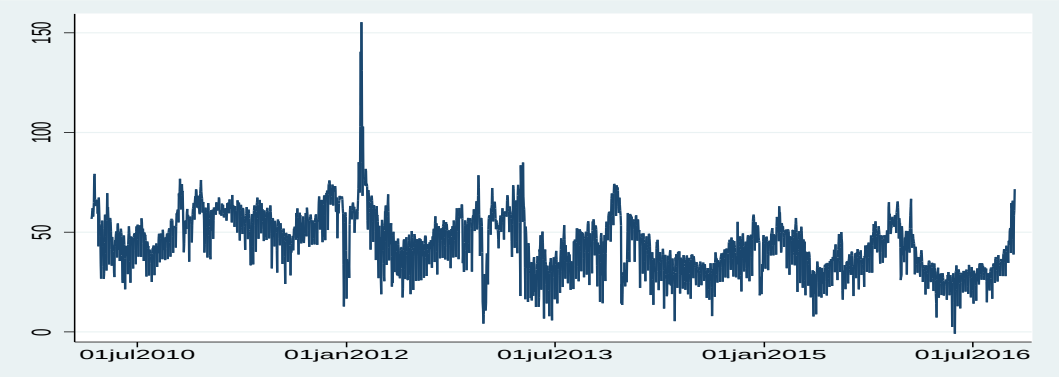
Table 5.3: Descriptive statistics of electricity volumes: 28/3/13–25/6/13 and 27/6/13–24/9/13

	Pre-intraday period	Post-intraday period
Mean	2217.17	2292.77
Std. dev.	457.813	562.472
Min	949.5	934.2
Max	4305.6	4828.6
Skewness	0.590	0.508
Kurtosis	3.888	3.429
Obs.	2159	2160

This table presents the descriptive statistics of the data used in the volume volatility and volume level analysis based on realized variance measures and t-tests.

24 hours of one day so we use daily instead of hourly data as is the case in the first approach. The development of the day-ahead spot electricity prices is illustrated in Figure 5.3.

Figure 5.3: Swissix Day Base Index (EUR/MWh): 3/3/10–19/10/16



This figure presents the development of the Swissix Day Base Index on the day-ahead market from March 3, 2010 to October 19, 2016.

Source: authors and data from the EPEX SPOT.

Table 5.4 contains the descriptive statistics for the original, deseasonalised and IHS-transformed price series. We start the empirical analysis by detecting outliers in the original price series. In line with literature, we filter values that exceed three times the standard deviation of the original price series (Ketterer 2014; Gianfreda 2010; Mugele *et al.* 2005).[2] The outliers are replaced with the value of three times the standard deviation for the respective weekday.

[2]The standard deviation is calculated individually for all seven weekdays to compare like with like. For example, a Monday is compared with the mean and standard deviation of all Mondays in the sample (Bierbrauer *et al.* 2007).

Table 5.4: Descriptive statistics of the original price series, deseasonalised series and IHS-transformed deseasonalised series for: 3/3/10–19/10/16

	Original price	Deseasonalised	IHS deseasonalised
Mean	44.510	44.510	4.447
Std. dev.	14.544	11.212	0.357
Max	155.320	86.583	5.154
Min	-0.910	-7.631	-2.730
Skewness	0.442	-0.074	-7.183
Kurtosis	5.277	3.450	119.107
Obs.	2423	2423	2422

This table presents the descriptive statistics of the original price series, deseasonalised series and IHS-transformed deseasonalised series from March 3, 2010 to October 19, 2016. The latter series is used in the analysis of price volatility based on GARCH modeling.

After smoothing outliers, the seasonal cycle is removed from the time series. Similar to Ketterer (2014), we consider $P_t = y_t + s_t$, i.e. the observed price P_t comprises the stochastic part y_t and a seasonal component s_t. The average electricity price varies across the week because of changes in the electricity demand. The price also follows a yearly pattern as the different seasons influence the electricity demand. We address weekly and yearly seasonalities by using constant step functions which consist of dummies for each cycle (Trück & Weron 2004). Dummies for week days, d_i, and months, m_j, are included in the following function to capture seasonality

$$s_t = c + \sum_{i=1}^{7} \xi_i d_i + \sum_{j=1}^{12} \nu_j m_j. \tag{5.1}$$

The results of the deseasonalisation are shown in Table 5.5. The coefficients for weekday dummies illustrate that the price remains high at the beginning of the week, declines from Friday onward, and reaches its minimum on Sundays. Not all monthly dummies are significant, but we observe a relevant electricity price reduction in April through September. Prices are highest during winter (December–February) and lowest in May and during the summer (June–August).

We deduct the seasonal components from the original price series and align the means of both series. Finally, we apply the IHS transformation to the deseasonalised price series and employ the resulting series in the following analysis. The development of the deseasonalised electricity prices is illustrated in Figure

5.4.

Table 5.5: Removing seasonality

	Coefficient	p-value
c	51.731	< 0.0001
Tue	2.553	0.003
Wed	2.594	0.002
Thu	2.124	0.013
Fri	0.966	0.259
Sat	-5.713	< 0.0001
Sun	-13.351	< 0.0001
Feb	3.713	0.002
Mar	-1.492	0.185
Apr	-8.854	< 0.0001
May	-14.274	< 0.0001
Jun	-13.948	< 0.0001
Jul	-12.316	< 0.0001
Aug	-12.750	< 0.0001
Sep	-7.278	< 0.0001
Oct	-0.351	0.758
Nov	1.460	0.215
Dec	2.017	0.084

This table presents the results of the deseasonalisation – OLS regression with the Swissix Day Base price, corrected for outliers, as dependent variable. Monday and January are used as reference variables.

Figure 5.4: Swissix Day Base Index (deseasonalised) (EUR/MWh): 3/3/10–19/10/16



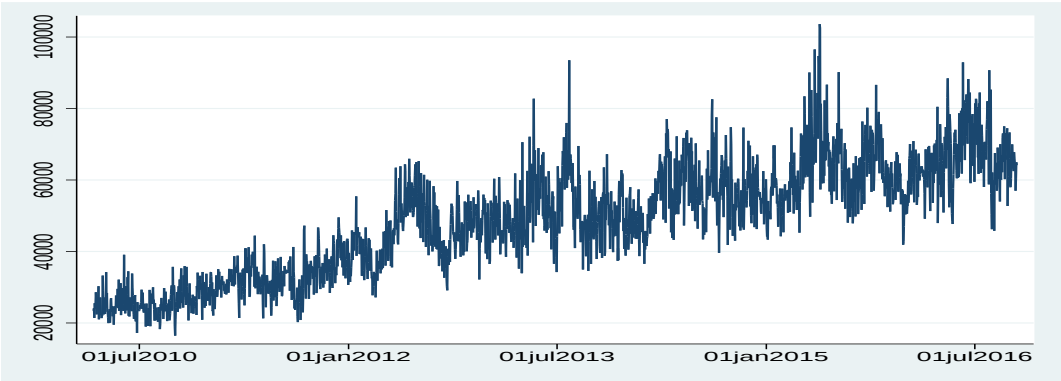
This figure presents the development of the deseasonalised Swissix Day Base Index on the day-ahead market from March 3, 2010 to October 19, 2016.

Source: authors and data from the EPEX SPOT.

For the volume volatility analysis based on GARCH modeling we use daily

EPEX SPOT Auction Market volume from March 3, 2010 to October 19, 2016, i.e. a total of 2423 observations. The development of the electricity volumes is illustrated in Figure 5.5, where we can observe a clearly defined trend. Hence, we will be using first differences after taking the log of the volume series.

Figure 5.5: EPEX SPOT Auction Market Volume (MWh): 3/3/10–19/10/16



This figure presents the development of the EPEX SPOT Auction Market volume from March 3, 2010 to October 19, 2016.

Source: authors and data from the EPEX SPOT.

Table 5.6: Descriptive statistics of the original volume series, log series and demeaned log differences for: 3/3/10–19/10/16

	Original volume	Log volume	Demeaned differences
Mean	48735.2	10.738	0.001
Std. dev.	15500.8	0.347	0.133
Max	103601.5	11.548	0.688
Min	16456.2	9.708	-0.559
Skewness	0.072	-0.527	0.105
Kurtosis	2.343	2.393	4.365
Obs.	2423	2423	2422

This table presents the descriptive statistics of the original volume series, log series and demeaned log differences for a period from March 3, 2010 to October 19, 2016.

A regression of electricity volume on weekday and month dummy variables reveals a weak seasonal component, with only 3 month dummies (May–July) being statistically significant. Therefore, in order to take into account seasonal patterns, we apply the demeaning procedure described in Chapter 4, whereby we subtract the median log difference for each day of the year from each log difference. Table 5.6 contains the descriptive statistics for the original volume series, log series and demeaned log differences.

Chapter 6

Empirical results

Based on the existing literature on intraday electricity markets, we have developed the hypothesis that the introduction of intraday trading should lead to a decrease in price volatility on the day-ahead market. Similarly, our second hypothesis is that volume volatility on the day-ahead market should decrease after the launch of intraday trading. In the absence of an intraday market, the day-ahead auction is the closest market to real time that is available to participants. Therefore, there is a 24-hour period between trading and delivery, when participants are not able to respond to any changes in, for example, forecasts, and optimize power plant usage or consumer demand. Because prices and total volume on the day-ahead market are determined at the intersection of the aggregated demand and supply curves, these prices and volumes are formed by forecasted generation and consumption of electricity, which will most likely differ from the actual generation and consumption at real time. Due to the development of renewable energy in Europe, the production of power varies more and more within the day or even the hour, and forecast errors, i.e. deviations between forecasted and actual production, can become quite significant. In anticipation of this, market participants might revise their forecasted demand or supply upwards or downwards, in order to account for the inaccuracy of day-ahead forecasts and the risk of power plant outages. However, with an intraday market, participants can use the day-ahead auction to trade volumes forecasted based on "normal" assumptions, and then adjust for any "abnormal" deviations in the intraday market. Thus, our intuition is that prices and volumes on the day-ahead market would fluctuate less in the presence of an intraday market that is closer to delivery time.

In addition, we speculate that participants who prefer to trade as close to

delivery time as possible or want to take advantage of arbitrage opportunities with neighboring countries, will switch from the day-ahead market to the intraday market. Therefore, our third hypothesis is that the level of electricity volume traded in day-ahead auctions should decrease after the introduction of intraday trading.

The remainder of this chapter is structured as follows: three sections based on the time series being analyzed (the volatility of electricity prices, the volatility of traded electricity volumes or electricity volumes), followed by a concluding section where we discuss our results. Within the next two sections, we first look at the differences between the two periods before and after the intraday market introduction and infer what was the impact of the introduction of the intraday market. Then, we estimate a GARCH(1,1) model for an alternative approach of identifying the impact of the introduction of the intraday market. In the third section that covers the level of traded electricity, we directly discuss this impact.

6.1 Volatility of electricity prices on the day-ahead market

6.1.1 Realized variance measures and t-test

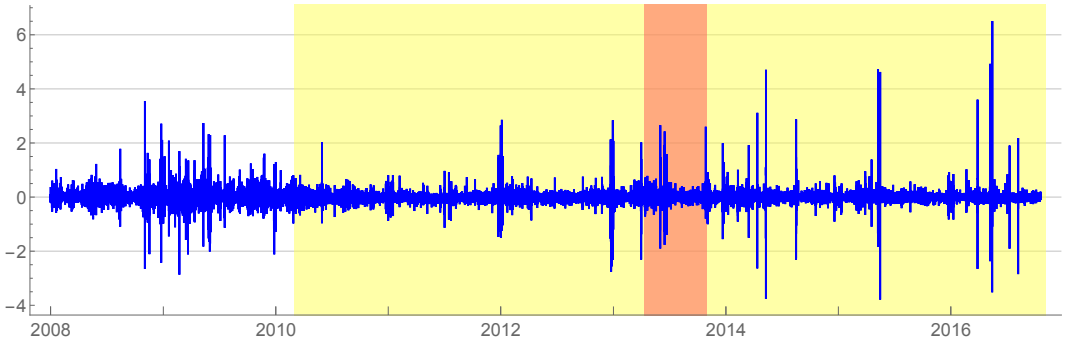
We base our analysis on the intuition used by Ritter *et al.* (2015): to find comparable time periods before and after the launch of the intraday electricity market in Switzerland on June 26, 2013, we work on the assumption that the closer the compared periods, the greater their comparability. Therefore, in the same manner as Ritter *et al.* (2015), we compare a 90-day period before the launch of the intraday market which starts on March 28, 2013 with a period of 90 days after the launch ending on September 24, 2013.

We discuss not only intraday and daily returns, but also standardized daily returns (r_t/RVO_t and $r_t/\sqrt{RBV_t}$). According to Lunde & Olesen (2014), who analyze intraday transaction records from NASDAQ OMX Commodities Europe, returns standardized by realized volatility have an empirically close to normal distribution. However, this goes against our assumption made in Chapter 4 about the presence of jumps – if they are present, we expect the normality of standardized returns to be violated due to the bias in RVO_t caused by microstructure noise and jumps (see e.g. Andersen *et al.* 2010b). The detected

presence of jumps in Andersen *et al.* (2007), Ciarreta & Zarraga (2016) and Huang & Tauchen (2005), among others, can then be explained by the fact that there can be a bias in realized volatility estimates (Andersen *et al.* 2010b). At the same time, we expect the distribution of $r_t/\sqrt{RBV_t}$ to be close to standard normal as realized bipower variation is an estimator of the integrated variance which is robust to the presence of jumps. We perform all the tests (t-tests or Jarque–Bera Adjusted Lagrange Multiplier (ALM), among others) at the 0.05 significance level if not stated otherwise.

Figure 6.1 shows the hourly logarithmic returns for electricity prices, $r_{t,i}$, on the Swiss day-ahead market from January 1, 2008 to October 19, 2016.

Figure 6.1: Hourly price logarithmic returns on the Swiss day-ahead market: 1/1/08–19/10/16



This figure presents the development of hourly price logarithmic returns, $r_{t,i}$, on the Swiss day-ahead market from January 1, 2008 to October 19, 2016. For the first approach, we use data from March 28, 2013 to June 25, 2013 and from June 27, 2013 to September 24, 2013 (indicated by red background; including June 26, 2013). For the second approach, we use data from March 3, 2010 to October 19, 2016 (indicated by yellow background).

Source: authors' computations and data from the EPEX SPOT.

The highest hourly price logarithmic return over the period from January 1, 2008 to October 19, 2016 was on May 15, 2016 (17:00–18:00) which is the same day as the minimum price was observed and also the day with the highest number of negative prices within one day. This return was equal to roughly 651%. The lowest return was observed on March 30, 2008 (2:00–3:00) and was equal to approximately -454%.

Using the prices from the 90-day period before the Swiss intraday market introduction (March 28, 2013 to June 25, 2013[1]), we calculate hourly returns, $r_{t,i}$,

[1]Within the period, we do not have data points for two consecutive logarithmic returns, i.e. one price observation. We replace the two missing values with the average value of the preceding and following returns. This should not have any tangible effect on the results of

daily returns, r_t, as well as standardized daily returns, r_t/RVO_t and $r_t/\sqrt{RBV_t}$. In Table 6.1, we provide the descriptive statistics of all of these.

Table 6.1: Descriptive statistics of $r_{t,i}$, r_t, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity prices: 28/3/13–25/6/13

	$r_{t,i}$	r_t	r_t/RVO_t	$r_t/\sqrt{RBV_t}$
Mean	$-5.593 \cdot 10^{-4}$	-0.013	-0.032	-0.034
Std. dev.	0.213	0.244	0.536	0.610
Min	-2.311	-0.656	-1.543	-1.551
Max	2.658	0.928	1.582	1.50
Skewness	1.308	0.655	0.165	-0.007
Kurtosis	49.674	4.685	4.264	3.629
Obs.[2]	2160	90	90	90

This table presents the descriptive statistics of hourly returns, $r_{t,i}$, daily returns, r_t, as well as standardized daily returns, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity prices from March 28, 2013 to June 25, 2013.

The kurtosis of 49.674 indicates that the distribution of hourly returns is highly leptokurtic, with thicker tails and values concentrated around the mean. Based on the skewness of 1.308, the distribution is highly right-skewed which means that the right tail is longer and most of the distribution is on the left. The highest hourly negative return is 231.1%, which is 10.9 standard deviations away from the mean. The highest hourly positive return is 265.8%, which is roughly 12.6 standard deviations away from the mean.

On the basis of skewness and kurtosis, the non-standardized daily returns do not seem to be normally distributed. The kurtosis of 4.685 indicates leptokurtic distribution and the skewness of 0.655 again suggests that the distribution is moderately right-skewed. The highest daily negative return is 65.6% and the highest daily positive return is 92.8%. We present a quantile-quantile plot for daily price returns in Figure A.1.

When we standardize the daily returns by both realized volatility and the square root of bipower variation, we can see that the distribution of these standardized returns is closer to normal. The distributions of r_t/RVO_t and of $r_t/\sqrt{RBV_t}$ are almost symmetric (skewness of 0.165 and -0.007, respectively). The kurtosis of 4.264 for r_t/RVO_t and of 3.629 for $r_t/\sqrt{RBV_t}$ is also closer to a mesokurtic distribution when compared to non-standardized daily returns.

our analysis as these two data points are around 0.09% of all our data points for price returns in the pre-intraday market period.

[2]We treat the two missing and subsequently replaced returns as if they were in the original dataset.

In Table A.1, we present the results of the Jarque–Bera ALM goodness-of-fit test for r_t, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for both periods as proposed by Urzúa (1996) with the null hypothesis that the data was drawn from a normal distribution and the alternative hypothesis that it was not. This test effectively compares the skewness and kurtosis of our data to a normal distribution. A p-value of 0.005 implies that it is highly unlikely that non-standardized daily returns within the pre-intraday market period came from a normal distribution. In case of r_t/RVO_t, we also reject the null hypothesis (p-value of 0.041), but we were not able to reject the null hypothesis in case of $r_t/\sqrt{RBV_t}$ (p-value of 0.276).

The descriptive statistics of returns for the period after the intraday market introduction (from June 27, 2013 to September 24, 2013) can be found in Table 6.2.

Table 6.2: Descriptive statistics of $r_{t,i}$, r_t, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity prices: 27/6/13–24/9/13

	$r_{t,i}$	r_t	r_t/RVO_t	$r_t/\sqrt{RBV_t}$
Mean	$5.64 \cdot 10^{-4}$	0.014	0.033	0.083
Std. dev.	0.077	0.154	0.498	0.706
Min	-0.453	-0.349	-1.229	-1.391
Max	0.550	0.491	1.349	2.967
Skewness	0.836	0.397	0.014	0.848
Kurtosis	12.144	3.884	2.754	5.295
Obs.	2160	90	90	90

This table presents the descriptive statistics of hourly returns, $r_{t,i}$, daily returns, r_t, as well as standardized daily returns, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity prices from June 27, 2013 to September 24, 2013.

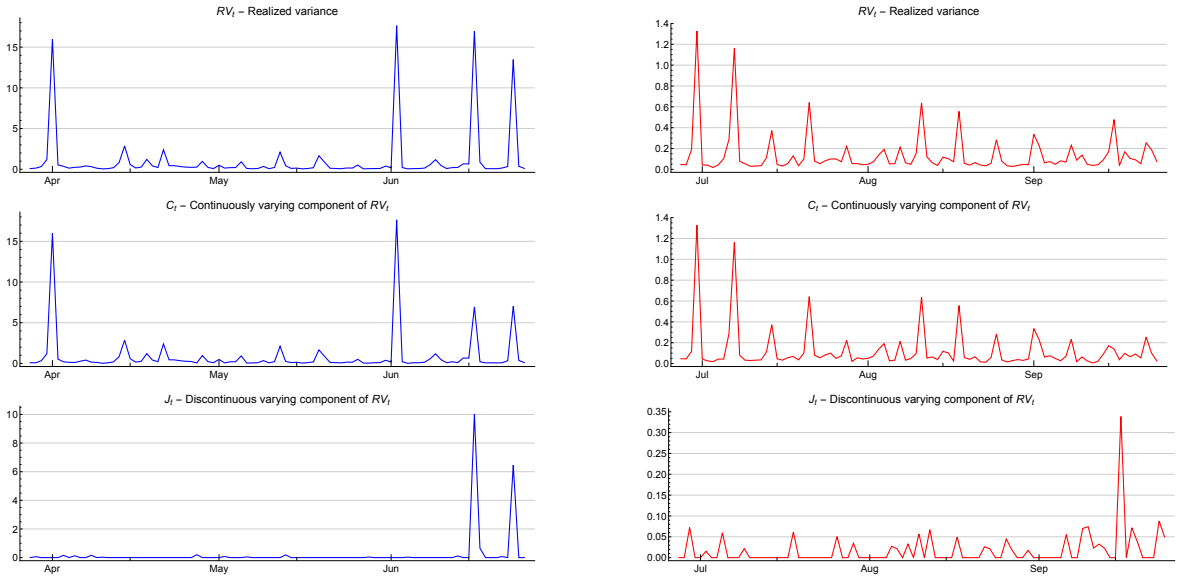
The kurtosis of 12.144 indicates a leptokurtic distribution. Based on the skewness of 0.836, the distribution is moderately right-skewed. The highest hourly negative return is 45.3%, which is almost 5.9 standard deviations away from the mean. The highest positive hourly return is 55%, which is approximately 7.1 standard deviations away from the mean.

The skewness of 0.397 and kurtosis of 3.884 suggest that daily non-standardized returns are close to normally distributed (approximately symmetric mesokurtic distribution). The highest daily negative return is 34.9% and the highest daily positive return is 49.1%. A quantile-quantile plot for daily price returns for the post-intraday market period is again presented in Figure A.1.

The distribution of r_t/RVO_t with a skewness of 0.014 and kurtosis of 2.754

seems to be closer to normal when compared to non-standardized returns. The opposite can be said for the distribution of $r_t/\sqrt{RBV_t}$ with a skewness of 0.848 and kurtosis of 5.295. We can see in Table A.1 that based on the p-value of 0.049, the null hypothesis of the Jarque–Bera ALM test is rejected at the 5% level, suggesting that the non-standardized daily returns do not come from a normal distribution. The same can be said for $r_t/\sqrt{RBV_t}$ with a p-value of 0.002. We were not able to reject the null in the case of r_t/RVO_t (p-value of 0.926).

Figure 6.2: Realized variance and variation components of electricity prices on the Swiss day-ahead market



We use hourly log-returns of electricity prices on the Swiss day-ahead market to compute daily realized variance along with its component. The three graphs on the left side (blue) relate to the period before the introduction of the intraday market. The three graphs on the right side (red) relate to the period after the introduction of the intraday market.

Source: authors' computations and data from the EPEX SPOT.

Figure 6.2 shows the realized variance and its decomposition into continuous and jump parts for both periods. The largest jump contribution during the period before the intraday market introduction was on June 16, 2013 and was equal to almost 10.031. According to The Economist (2013), on that day, the wholesale electricity price in Germany's electricity market fell to -100 EUR/MWh (the lowest price on that day in the day-ahead market in Switzerland was 0 EUR/MWh): "Demand was low. Between 2pm and 3pm, solar and wind generators produced 28.9 gigawatts (GW) of power, more than half the total. The grid at that time could not cope with more than 45GW without

becoming unstable. At the peak, total generation was over 51GW; so prices went negative to encourage cutbacks and protect the grid from overloading." EPEX SPOT SE (2013a) adds: "The negative prices stem from fundamentals marked by (1) low industrial consumption on Sunday, (2) low residential consumption on mild weather, and (3) abundant inflexible generation. The Day-Ahead market sent strong price indications signaling difficult balance conditions between (over) supply and (low) demand. [...] it is apparent that the abundance of non-flexible production combined with low electricity demand have caused high prevalence of negative prices on Sunday 16 June 2013." The largest jump contribution to the daily return variation during the period after the intraday market introduction was on September 16, 2013 and was equal to 0.339.

Graphs of jump components confirm the assertion of Huisman & Mahieu (2003) and Weron *et al.* (2004), among others, that jumps in electricity prices are typical for their short existence, i.e. prices fall back to a normal level sometimes after even one day (for example when the outage or severe weather conditions are over).

We also present in Figure A.3 the logarithms of RV_t for both periods and in Figure A.4 we present J_t using the 90^{th} percentile of the standard normal distribution for the detection of these jumps. In Table 6.3, we present the descriptive statistics of realized variance along with its components.

Table 6.3: Descriptive statistics of RV_t, C_t and J_t for electricity prices

	Pre-intraday period			Post-intraday period		
	RV_t	C_t	J_t	RV_t	C_t	J_t
Mean	1.087	0.882	0.205	0.141	0.124	0.017
Std. dev.	3.292	2.655	1.251	0.209	0.209	0.042
Min	0.046	0.015	0	0.018	0.006	0
Max	17.641	17.641	10.031	1.327	1.327	0.339
Skewness	4.339	5.181	6.89	3.819	3.978	5.440
Kurtosis	20.454	30.531	50.391	19.375	20.474	41.166
Obs.	90	90	90	90	90	90

This table presents the descriptive statistics of realized variance, RV_t, continuous component of realized variance, C_t, and jump component of realized variance, J_t, for electricity prices for both the pre-intraday market period and the post-intraday market period.

We can clearly see that the means of RV_t, C_t as well as J_t decreased considerably after the intraday market introduction with the mean of post-intraday market RV_t being less than 13% of the mean of pre-intraday market RV_t, the

mean of post-intraday market C_t being around 14% of the mean of pre-intraday market C_t and the mean of post-intraday market J_t being around 8% of the mean of pre-intraday market J_t.

Similarly to Andersen *et al.* (2010b), we compare in Table 6.4 the relative contribution of jumps to the realized variance (J_t/RV_t) for the period before and after the intraday market launch. During the period before the intraday market launch, there were 74 days without detected jumps (approximately 82% of all days). In the post-intraday period, there were 61 days without detected jumps, which is around 68% of all days. We can see that the mean of the relative jump component increased after the intraday market introduction from 9.8% to 17.3%. Taking into account the results in Table 6.3, we can therefore deduce that RV_t decreased significantly more than J_t. The maximum relative contribution of jumps increased from 77.8% to 84.6%.

Table 6.4: Relative jump contribution (J_t/RV_t) for electricity prices

	Pre-intraday period	Post-intraday period
Mean	0.098	0.173
Std. dev.	0.216	0.262
Min	0	0
Max	0.778	0.846
Obs.	90	90

This table presents the relative contribution of jumps to the realized variance (J_t/RV_t) for electricity prices for both the period before and after the intraday market introduction.

Although Welch's t-test does not assume the equality of variances, it maintains the normality assumption (Welch 1947). Therefore, before performing the t-test, we verify whether RV_t, C_t and J_t for both periods are normally distributed using the Cramér-von Mises test[3] as suggested by the Wolfram Mathematica software as the most powerful test of normality that applies to our data. The null hypothesis in this test is that RV_t, C_t and J_t are normally distributed and the alternative hypothesis is that they are not. Based on the very low p-values, which are reported along with the respective statistics in Table A.2, the null hypothesis is rejected at any reasonable level in all three cases for both periods. Consequently, we have to rely on the central limit theorem stating that the distribution of the two sample means for all three cases converges to the normal distribution as the sample sizes get large, regardless of the

[3]We do not mention the theory behind this test and rather refer to the article written by Darling (1957).

distributions of the underlying data. Therefore, if the sample size is sufficiently large, the normality assumption is satisfied. Ruxton (2006) states that the central limit theorem requires a combined sample size of at least 30. Needless to say that this depends on the specific data and its skewness or heavy-tailedness. We have a combined sample size of 180 (90 for both periods) so we consider the sample size to be large enough to rely on the central limit theorem.

The results of the t-test are presented in Table 6.5. Based on the corresponding p-values, the null hypothesis that the difference in true population means is less than or equal to 0 is rejected at the 0.05 significance level for RV_t and C_t. Therefore, we conclude that the alternative hypothesis, as stated in Chapter 4, is in case of RV_t and C_t true and we infer from this that the total price variance and its continuous component are lower in the period after the intraday market introduction. However, the null hypothesis is not rejected at the 0.05 significance level for J_t (but would be rejected at the 10 percent level).

Table 6.5: Unequal variance t-test: Pre-intraday period vs. Post-intraday period (RV_t, C_t and J_t for electricity prices)

	Statistic	*df*	p-value
RV_t	2.718	89.716	0.004
C_t	2.70	90.104	0.004
J_t	1.424	89.196	0.079

This table reports the results of the unequal variance t-tests for RV_t, C_t and J_t for electricity prices during the period before and after the intraday market introduction.

6.1.2 GARCH modeling

Before we estimate the GARCH model, we conduct some necessary unit root tests in the employed series in Table 6.6, in order to test for the presence of a stochastic trend in the autoregressive part of the series. The Augmented Dickey-Fuller (ADF) test (Dickey & Fuller 1981), the Dickey-Fuller GLS (DF-GLS) test (Elliott *et al.* 1996) and the Phillips-Perron (PP) test (Knittel & Roberts 2005) evaluate the null hypothesis of a unit root against an alternative of stationarity. We assume a constant, and select the optimal lag length based on the Bayesian information criterion (BIC). The null hypothesis of a unit root is rejected. Hence, it is not necessary to estimate the differences or returns.

The empirical estimates of the GARCH model in Equations 4.28 and 4.29 are presented in Table 6.7. The results reveal a strongly persistent process,

Table 6.6: Unit root tests for IHS-transformed deseasonalised price series: 3/3/10–19/10/16

	Coefficient	p-value
ADF	-9.079	< 0.0001
DF-GLS	-9.973	< 0.0001
PP	-15.395	< 0.0001

This table presents the results of the unit root tests: the Augmented Dickey-Fuller (ADF) test, the Dickey-Fuller GLS (DF-GLS) test and the Phillips-Perron (PP) test. All tests are conducted for the IHS-transformed deseasonalised price series from March 3, 2010 to October 19, 2016.

as the sum of α_1 and α_2 is close to 1. We may observe that the dummy variable coefficient γ is statistically significant and negative at the 5% level. Recall that the dummy variable takes the value 0 before the date of the launch of the intraday market, and 1 thereafter. Hence, we may conclude that the unconditional volatility of the electricity prices on the day-ahead market has decreased as a result of the introduction of the intraday market.

Table 6.7: GARCH(1,1) model estimates with dummy variable for IHS-transformed deseasonalised price series: 3/3/10–19/10/16

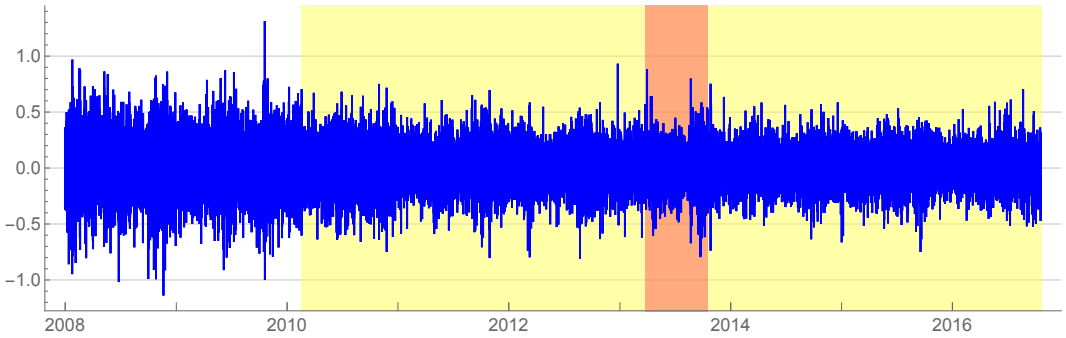
	Coefficient	Std. err.	p-value
Mean equation			
β_0	4.486	0.003	< 0.0001
Variance equation			
α_0	-4.568	0.101	< 0.0001
α_1	0.860	0.044	< 0.0001
α_2	0.109	0.022	< 0.0001
γ	-0.243	0.110	0.028

This table reports the empirical estimates of the GARCH(1,1) model with dummy variable for IHS-transformed deseasonalised price series from March 3, 2010 to October 19, 2016.

6.2 Volatility of traded volume of electricity on the day-ahead market

We employ the same procedure to analyzing the volatility of traded volume. Figure 6.3 depicts the hourly logarithmic electricity volume changes, $r_{t,i}$, on the Swiss day-ahead market from January 1, 2008 to October 19, 2016.

Figure 6.3: Hourly price logarithmic changes on the Swiss day-ahead market: 1/1/08–19/10/16



This figure presents the development of hourly volume logarithmic changes, $r_{t,i}$, on the Swiss day-ahead market from January 1, 2008 to October 19, 2016. Again, the period used for the analysis employing the realized variance measure and t-test is indicated by red background and the period used for the analysis employing GARCH modeling is indicated by yellow background.

Source: authors' computations and data from the EPEX SPOT.

The lowest hourly logarithmic change over the period from January 1, 2008 to October 19, 2016 was on November 19, 2008 and was equal to roughly -114% (20:00–21:00). The highest change was on October 19, 2009 and was equal to 131% (7:00–8:00).

We approach the analysis of the volatility of the traded volume of electricity on the Swiss day-ahead market in the same manner as in the already described analysis of the volatility of electricity prices.

6.2.1 Realized variance measures and t-test

We calculated $r_{t,i}$, r_t, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity volumes from March 28, 2013 to June 25, 2013[4]. We present their descriptive statistics in Table 6.8.

The kurtosis of 7.514 suggests a leptokurtic distribution and the skewness of 0.099 indicates an approximately symmetrical distribution of hourly volume changes. The lowest difference is equal to -60.4%, which is roughly 5.3 standard deviations away from the mean. The highest hourly positive difference is 88.2%, which is approximately 7.7 standard deviations away from the mean.

The kurtosis of 3.240 indicates a rather mesokurtic distribution of daily

[4]Within this period, we do not have data points for two consecutive logarithmic changes. Again, we replace the two missing values with the average value of the preceding and following changes.

Table 6.8: Descriptive statistics of $r_{t,i}$, r_t, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity volumes: 28/3/13–25/6/13

	$r_{t,i}$	r_t	r_t/RVO_t	$r_t/\sqrt{RBV_t}$
Mean	$2.150 \cdot 10^{-4}$	0.005	0.014	0.052
Std. dev.	0.114	0.278	0.502	0.746
Min	-0.604	-0.572	-1.0	-1.375
Max	0.882	0.879	1.055	3.216
Skewness	0.099	0.185	-0.022	1.265
Kurtosis	7.514	3.240	2.282	6.882
Obs.[5]	2160	90	90	90

This table presents the descriptive statistics of hourly changes, $r_{t,i}$, daily changes, r_t, as well as standardized daily changes, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity volumes from March 28, 2013 to June 25, 2013.

changes and the skewness of 0.185 suggests that the distribution is roughly symmetrical. The lowest daily change is -57.2% and the highest daily change is 87.9%. We present a quantile-quantile plot for daily volume changes in Figure B.1. The distribution of standardized returns, specifically of r_t/RVO_t, is also symmetrical, but the kurtosis of 2.282 suggests a rather platykurtic distribution. The distribution of $r_t/\sqrt{RBV_t}$ is highly skewed (skewness of 1.265) and leptokurtic (kurtosis of 6.882). In Table B.1, we present the results of the Jarque–Bera ALM test for daily electricity volume changes. Based on the p-values, we cannot reject the null hypothesis in cases of both r_t and r_t/RVO_t (p-values of 0.574 and 0.319, respectively). The null hypothesis can be rejected for $r_t/\sqrt{RBV_t}$ so we can again imply that these changes do not come from a normal distribution (the null hypothesis is rejected at any reasonable level).

The corresponding descriptive statistics for electricity volumes from June 27, 2013 to September 24, 2013 can be found in Table 6.9. In contrast to the electricity volumes in the pre-intraday market period, we have all the data points in the post-intraday market period.

The kurtosis of 7.227 indicates a leptokurtic distribution and the skewness of -0.150 suggests roughly a symmetrical distribution. The highest hourly negative difference is 79.6%, which is roughly 6.3 standard deviations away from the mean. The highest hourly positive difference is 80%, which is approximately 6.3 standard deviations away from the mean.

The skewness of -0.176 and kurtosis of 3.163 suggest that daily changes are close to normally distributed (approximately symmetric mesokurtic distribution). The highest daily negative change is 62.1% and the highest daily positive

Table 6.9: Descriptive statistics of $r_{t,i}$, r_t, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity volumes: 27/6/13–24/9/13

	$r_{t,i}$	r_t	r_t/RVO_t	$r_t/\sqrt{RBV_t}$
Mean	0.0001	0.003	0.001	-0.019
Std. dev.	0.126	0.237	0.442	0.582
Min	-0.796	-0.621	-1.309	-2.359
Max	0.80	0.534	1.092	1.507
Skewness	-0.150	-0.176	-0.289	-0.880
Kurtosis	7.227	3.163	3.821	5.724
Obs.	2160	90	90	90

This table presents the descriptive statistics of hourly changes, $r_{t,i}$, daily changes, r_t, as well as standardized daily changes, r_t/RVO_t and $r_t/\sqrt{RBV_t}$ for electricity volumes from June 27, 2013 to September 24, 2013.

change is 53.4%. The quantile-quantile plot for daily volume changes can again be found in Figure B.1. Based on the skewness and kurtosis, the distribution of both standardized changes r_t/RVO_t and $r_t/\sqrt{RBV_t}$ is not close to the normal distribution. Based on the results of the Jarque–Bera ALM test in Table B.1, the null hypothesis can be rejected only in the case of $r_t/\sqrt{RBV_t}$. In case of r_t and r_t/RVO_t, the null hypothesis cannot be rejected at the 5% level.

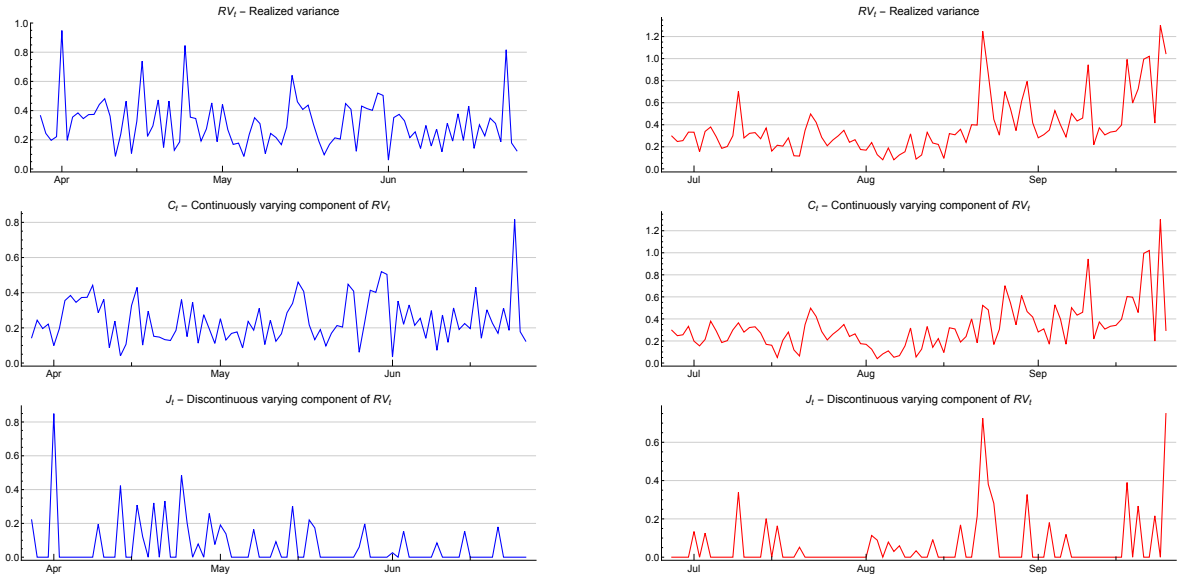
The realized variance and its continuous and jump parts are depicted in Figure 6.4. The largest jump contribution during the 90-day period before the intraday market introduction was on April 1, 2013 and was equal to almost 0.85. During the period after the intraday market introduction the largest jump contribution occurred on September 24, 2013 and was equal to approximately 0.75. We also present in Figure B.3 the logarithms of RV_t for both periods.

In Figure B.4, we present the graph of jump components of RV_t using the 90^{th} percentile of the standard normal distribution for the detection of these jumps. In Table 6.10, we present the descriptive statistics of realized variance and its components.

We compare in Table 6.11 J_t/RV_t for the periods before and after the intraday market launch. There were 63 days without detected jumps during the pre-intraday market period (70% of all days) and there were 65 days without detected jumps in the period after the introduction of the intraday market (approx. 72% of all days). We can see that the mean value decreased from 15.9% to 13.6% and that the maximum value decreased as well, specifically from 91.2% to 76.5%.

Again, before performing the t-test, we first test the normality of RV_t, C_t

Figure 6.4: Realized variance and variation components of electricity volumes on the Swiss day-ahead market



The three graphs on the left side (blue) relate to the period before the introduction of the intraday market. The three graphs on the right side (red) relate to the period after the introduction of the intraday market.

Source: authors' computations and data from the EPEX SPOT.

Table 6.10: Descriptive statistics of RV_t, C_t and J_t for electricity volumes

	Pre-intraday period			Post-intraday period		
	RV_t	C_t	J_t	RV_t	C_t	J_t
Mean	0.311	0.244	0.067	0.384	0.322	0.061
Std. dev.	0.168	0.130	0.136	0.257	0.216	0.139
Min	0.061	0.034	0	0.082	0.040	0
Max	0.949	0.817	0.850	1.303	1.303	0.750
Skewness	1.363	1.163	2.983	1.724	1.978	3.111
Kurtosis	5.676	5.675	14.544	5.729	8.402	13.803
Obs.	90	90	90	90	90	90

This table presents the descriptive statistics of realized variance, RV_t, continuous component of realized variance, C_t, and jump component of realized variance, J_t, for electricity volumes for both the pre-intraday market period and the post-intraday market period.

Table 6.11: Relative jump contribution (J_t/RV_t) for electricity volumes

	Pre-intraday period	Post-intraday period
Mean	0.159	0.136
Std. dev.	0.256	0.227
Min	0	0
Max	0.912	0.765
Obs.	90	90

This table presents the relative contribution of jumps to the realized variance (J_t/RV_t) for electricity volumes for the period before and after the intraday market introduction.

and J_t using Cramér-von Mises test. Based on the results presented in Table B.2, the null hypothesis is rejected at any reasonable level in all three cases for both periods so we have to rely on the central limit theorem. The results of the t-test are presented in Table 6.12.

Table 6.12: Unequal variance t-test: Pre-intraday period vs. Post-intraday period (RV_t, C_t and J_t for electricity volumes)

	Statistic	*df*	p-value
RV_t	-2.247	153.06	0.987
C_t	-2.933	145.831	0.998
J_t	0.258	177.915	0.398

This table reports the results of the unequal variance t-tests for RV_t, C_t and J_t for electricity volumes traded during the period before and after the intraday market introduction.

Based on the p-values, the null hypothesis that the difference in true population means is less than or equal to 0 cannot be rejected in any of the three cases at any reasonable level. Therefore, we cannot conclude that the intraday market introduction had any significant impact on the volatility of volumes or on any of the two components of realized volatility.

6.2.2 GARCH modeling

We employ the demeaned series of volume log differences in estimating the GARCH(1,1) model. We specify the mean equation based on the BIC, which suggests the AR(6) as the optimal model specification. Accordingly, the mean equation is presented as

$$v_t = \beta_0 + \sum_{i=1}^{6} \beta_i v_{t-i} + \epsilon_t \tag{6.1}$$

The empirical estimates for the GARCH model are presented in Table 6.13. The results reveal a strongly persistent process as the sum of α_1 and α_2 is close to 1. All six autoregressive variables are significant at the 5% level. We may observe again that the dummy variable coefficient γ is negative, however statistically insignificant at the 5% level. Hence, although we observe a decrease in volume volatility on the day-ahead market as a result of the introduction of the intraday market, this impact has not been significant.

Table 6.13: GARCH(1,1) model estimates with dummy variable for demeaned log differences in volume series: 3/3/10–19/10/16

	Coefficient	Std. err.	p-value
Mean equation			
β_0	0.001	0.002	0.549
β_1	-0.498	0.020	< 0.0001
β_2	-0.358	0.022	< 0.0001
β_3	-0.281	0.024	< 0.0001
β_4	-0.262	0.024	< 0.0001
β_5	-0.273	0.023	< 0.0001
β_6	-0.136	0.021	< 0.0001
Variance equation			
α_0	-7.415	0.303	< 0.0001
α_1	0.036	0.008	< 0.0001
α_2	0.923	0.017	< 0.0001
γ	-0.139	0.087	0.111

This table reports the empirical estimates of the GARCH(1,1) model with dummy variable for demeaned log differences in volume series from March 3, 2010 to October 19, 2016.

6.3 Traded volume of electricity on the day-ahead market

As in the cases of price volatility and volume volatility, we analyze the impact of the intraday market introduction on traded volume. Hourly volumes of electricity traded on the Swiss day-ahead market for the period from January 1, 2008 to October 19, 2016 were already presented in Figure 5.2. Again, we

use the period of 90 days before and after the intraday market introduction for the purpose of the t-test.[6]

In Table 6.14, we present the descriptive statistics of demeaned differences of traded electricity volume, V_d, in both the 90-day period from March 28, 2013 to June 25, 2013 and the 90-day period from June 27, 2013 to September 24, 2013.

Table 6.14: Descriptive statistics of demeaned differences of traded electricity volume: 28/3/13–25/6/13 and 27/6/13–24/9/13

	Pre-intraday period	Post-intraday period
Mean	0.608	-0.198
Std. dev.	246.684	289.815
Min	-1474.1	-2371.7
Max	1448.5	1869.5
Skewness	-0.048	-0.250
Kurtosis	6.891	8.691
Obs.	2158	2160

This table presents the descriptive statistics of demeaned differences of traded electricity volume for both the period before and after the intraday market introduction.

On the basis of very low p-values resulting from the tests of normality of the data reported in Table 6.15, we again have to rely on the central limit theorem. We have a combined sample size of 4318 which should be sufficient to rely on the central limit theorem.

Table 6.15: Cramér-von Mises goodness-of-fit test: demeaned differences of traded electricity volume

	Pre-intraday period		Post-intraday period	
	Statistic	p-value	Statistic	p-value
V_d	5.636	< 0.0001	6.247	< 0.0001

This table presents the results of the Cramér-von Mises goodness-of-fit test for demeaned differences of traded electricity volume. The null hypothesis in this test is that series of V_d is normally distributed and the alternative hypothesis is that it is not.

In Table 6.16, we present the results of the unequal variance t-test for demeaned differences of traded electricity volumes.

[6] In the pre-intraday market period, we do not have a data point for electricity volume, specifically on March 31, 2013 for hour 02:00–03:00. In the post-intraday market period, we have all the data points for electricity volumes.

Table 6.16: Unequal variance t-test: Pre-intraday period vs. Post-intraday period (volumes)

	Statistic	df	p-value
V_d	0.098	4209.79	0.461

This table reports the results of the unequal variance t-test for V_d during the period before and after the intraday market introduction.

The null hypothesis cannot be rejected at any reasonable level as the p-value is equal to 0.461. Therefore, we cannot conclude that the traded volume of electricity on the day-ahead market decreased after the intraday market introduction.

6.4 Discussion of results

Both statistical approaches we employed in our analysis support our hypothesis that price volatility on the day-ahead market decreased after the launch of the intraday market. We find that the total price variance and its continuous component were lower in the 90-day period after the intraday market introduction, when compared to the 90-day period before the launch of intraday trading. Total price variance decreased almost eight-fold and its continuous component decreased seven-fold. However, we cannot state that the jump component of price volatility, whose presence can be caused, for example, by fluctuations in demand, system breakdown, low elasticity of supply, severe weather conditions, transmission failures, and limited inventory capacities (see e.g. Huisman & Mahieu 2003; Weron *et al.* 2004), decreased after the intraday market introduction. On a longer time horizon, the coefficient of the dummy variable in the conditional variance equation of the GARCH model is negative and statistically significant, and indicates that the unconditional price volatility decreased by 24.3% since the introduction of the intraday market.

There is a noticeable difference in magnitude between the results yielded by the two statistical approaches, which is explained by several considerations. First, we attribute this difference to the fundamental distinctions between the two statistical methods employed, with GARCH being a parametric method while realized variance is nonparametric. Moreover, due to the nature of these methods, the measures of volatility we use differ as well – realized variance and its components vs. unconditional volatility. Second, while we use hourly

prices for the t-tests, we use daily prices in the GARCH estimation (which are arithmetic averages of the hourly prices). The frequency of the observations also contributes to the difference in the magnitude of the results, because unlike the GARCH model, the t-tests analyze the volatility within the day. Finally, we consider that the time horizons help explain the difference in magnitude: the t-tests cover a 180-day period (90 days before and after the launch of the intraday market), whereas in the GARCH model we use data covering roughly six and a half years. Thus, we reason that the effect of intraday trading introduction should be less pronounced over a longer time period, since the impact of intraday trading could be offset by other developments in the market.

At the same time, our hypothesis that volume volatility on the day-ahead market should decrease after the introduction of the intraday market is not supported by the results, as both statistical methods reveal that there has not been a significant change in volume volatility after the launch of intraday market. There are no statistically significant differences between the total volume variance, and its continuous and jump components before and after the launch of intraday trading. The coefficient of the dummy variable in the GARCH model, although negative, is also statistically insignificant. These results indicate that the presence of the intraday market has seemingly no effect on the fluctuation of electricity volume traded on the day-ahead market. We speculate that given the wholesale nature of these markets, the amounts of electricity supplied and demanded can be established in advance, and they are not as susceptible to forecast errors as prices are. Therefore, the opportunity to optimize electricity schedules in the 24 hours before delivery is more efficient in regard to pricing, rather than quantities traded.

Finally, our hypothesis that the level of traded volume would decrease after the intraday market was launched has not been confirmed either. This result supports our observation that the intraday market is of minor importance for trading and hedging and of higher importance for system security. The presence of the intraday market does not mean that a significant portion of participants will switch to it from the day-ahead market, given that the primary purpose of the intraday market is to allow participants to adjust their existing demand and supply schedules based on updated forecasts and new information.

We should also acknowledge that there are several potential disadvantages of the statistical methods we used in our analysis that might affect the interpretation of our results. In case of the first method used for the analysis (realized variance measures with subsequently used t-test), as mentioned in this chapter,

there can be a bias in realized volatility estimates (Andersen *et al.* 2010b). The unbiasedness of volatility measures is explored, for example, by Ciarreta *et al.* (2017). The results would also be more convincing if different estimators of integrated variance would be used and subsequently compared. Andersen *et al.* (2012), for example, propose two jump-robust estimators of integrated variance that allow for an asymptotic limit theory in the presence of jumps or Corsi *et al.* (2010) propose an estimator of integrated variance based on threshold bipower variation. However, as mentioned by Ciarreta *et al.* (2017): "Although each estimator has its own properties, there is no single method which is preferred to the rest."

Another problem can be with choosing the right t-test. We performed in this thesis directly the Welch's t-test (or unequal variance t-test) based on the widely accepted "rule" to avoid choosing the right statistical test based on the outcome of another test as described in Chapter 4. Despite the fact that Welch's t-test's power is similar to the power of the Student's t-test which assumes the equality of variances even in cases when the population variances are equal, there might have been cases in our analysis during which a use of the Student's t-test would be more suitable and would lead to slightly higher statistical power of the used test. We also again have to remind that we rely on the central limit theorem for the t-test's normality assumption to be satisfied. However, we believe that in all cases this approach is reasonable and well-grounded. We also mention potential extensions of this thesis in the next chapter.

The GARCH methodology we employ in the analysis has some conceptual limitations as well. One limitation is that while GARCH models work well under relatively stable market conditions due to their parametric nature, they might fail to capture irregular phenomena, such as wild market fluctuations, and other highly unanticipated events that can lead to significant structural change in the market. However, we believe that this should not influence our interpretation of the results because we have not identified any structural changes in the Swiss day-ahead electricity market during the analyzed period, and we have smoothed out all extreme prices resulting from temporary imbalances in supply and demand. A second limitation related to the first is that GARCH models often fail to fully capture the fat tails observed in asset return series. While heteroskedasticity can explain some of the fat tail behavior, it cannot explain all of it. One solution is to apply fat tail distributions, such as Student's t-distribution, although recent empirical studies of high-frequency financial time series indicate that the tail behavior of GARCH models remains too short even

with standardized Student's t innovations. Thus, the choice of the distribution is often a matter of trial and error and we believe that the distributional assumptions we made based on the related literature are appropriate for the analysis.

Finally, like the ARCH model family, GARCH models respond equally to positive and negative shocks, although in many markets, it has been empirically observed that future volatility responds differently to positive and negative price moves. This has led to the development of GARCH models that account for the asymmetry between up and down moves, such as the EGARCH model of Nelson (1991), or the Threshold GARCH (TGARCH) model, also known as the GJR-GARCH model following the work of Glosten *et al.* (1993). While asymmetric effects are encountered frequently in equity markets, we found little evidence of such effects occurring in electricity markets. Therefore, we believe that our use of the most basic GARCH(1,1) model is appropriate and in line with the literature.

Chapter 7

Conclusion

In this thesis we wanted to analyze the impact of the Swiss intraday electricity market introduction on the volatility of electricity prices, the volatility of traded volumes and on the level of traded volumes on the day-ahead market.

Using two statistical methods, t-tests for differences and GARCH modeling, we found that after the launch of intraday trading, price volatility has decreased while the volatility and level of traded electricity volume do not seem to have been affected in a statistically significant way.

A potential extension of this thesis could be to analyze whether the introduction of intraday auctions to the continuous intraday trading in Switzerland would lead to an improvement in market performance. Given that intraday auctions have not yet been launched in Switzerland, such a study could help establish the potential design of such auctions.

Another possible extension of this thesis would be to replicate the above analysis for other countries, since a deep analysis of the impact of the intraday electricity market introduction has not been done before not only for Switzerland, but also for other countries. As already mentioned, intraday electricity markets were launched in the Czech Republic in 2004 (Rodryc *et al.* 2012), in Germany in 2006, in France in 2007 (European Commodity Clearing 2015) and in Austria in 2012 (EPEX SPOT SE 2016b).

An extension of this thesis related to the first method used (realized variance measures with subsequently used t-test) would be to perform the same analysis also for a different window size, i.e. instead of comparing two 90-day periods, compare, for example, two 180-day periods.

In case of GARCH estimation, we do not control for any external variables that might affect the volatility of electricity prices or volumes. For instance, we

do not control for electricity generation by wind and photovoltaic, whose use, according to Kiesel & Paraschiv (2016), has led to a reduction in spot market prices by 6 EUR/MWh in 2010, with this decrease rising to 10 EUR/MWh in 2012. A potential extension of the thesis would be to replicate the analysis while controlling for these variables in order to establish whether the presence of intraday trading has the same impact on price volatility on the day-ahead market.

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Appendix A

Volatility of electricity prices

Table A.1: Jarque–Bera ALM goodness-of-fit test for daily electricity price returns: 28/3/13–25/6/13 and 27/6/13–24/9/13

	Pre-intraday period		Post-intraday period	
	Statistic	p-value	Statistic	p-value
r_t	20.447	0.005	6.523	0.049
r_t/RVO_t	8.263	0.041	0.147	0.926
$r_t/\sqrt{RBV_t}$	2.135	0.276	36.183	0.002

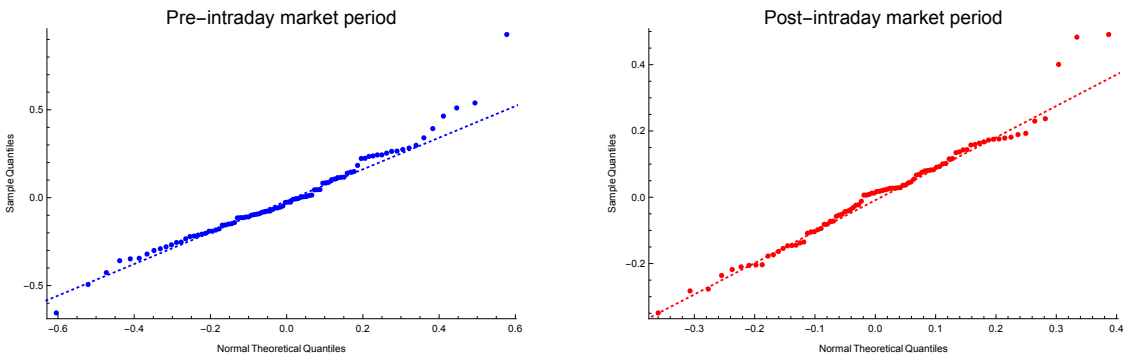
This table presents the results of the Jarque–Bera ALM goodness-of-fit test for daily electricity price returns for both the post-intraday market period and the pre-intraday market period. The null hypothesis in this test is that the data was drawn from a normal distribution and the alternative hypothesis that it was not.

Table A.2: Cramér-von Mises goodness-of-fit test: RV_t, C_t and J_t (price volatility)

	Pre-intraday period		Post-intraday period	
	Statistic	p-value	Statistic	p-value
RV_t	5.082	< 0.0001	2.70	< 0.0001
C_t	4.714	< 0.0001	2.966	< 0.0001
J_t	6.705	< 0.0001	2.854	< 0.0001

This table presents the results of the Cramér-von Mises goodness-of-fit test for RV_t, C_t and J_t for electricity prices. The null hypothesis in this test is that series of RV_t, C_t and J_t are normally distributed and the alternative hypothesis is that that they are not.

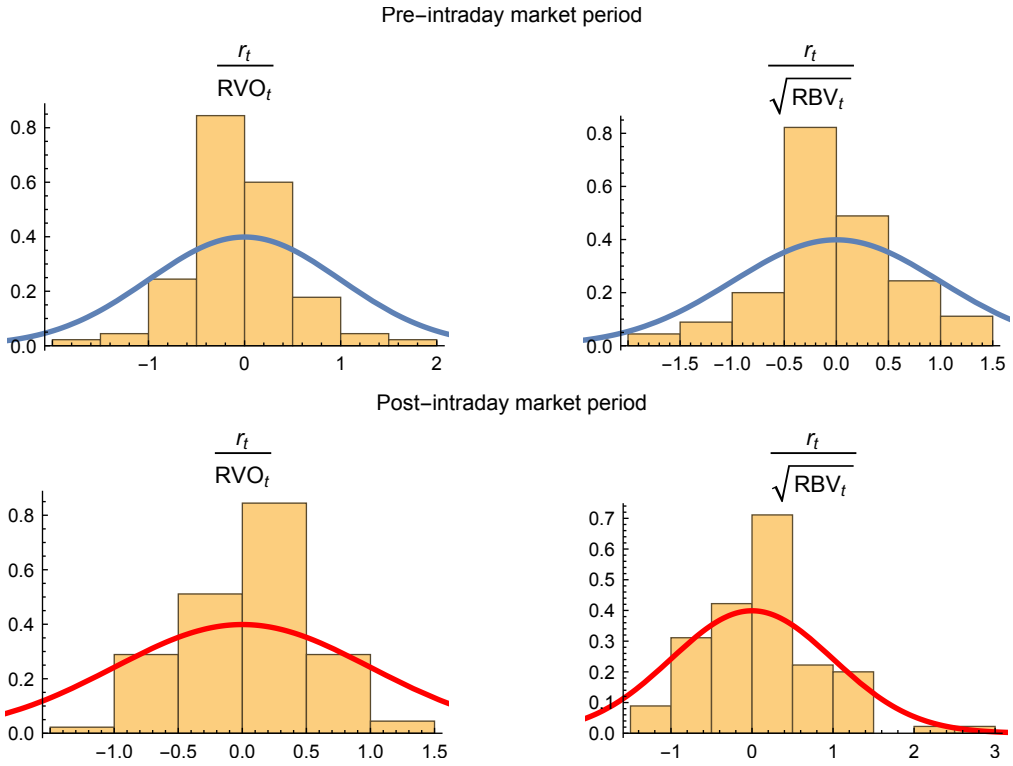
Figure A.1: Quantile-quantile plot for daily price returns



The figure presents QQ plot of the sample quantiles of daily price returns, r_t, versus theoretical quantiles from a normal distribution with the mean and variance equal to the mean and variance of the daily returns. The graph on the left/right side (blue/red) relates to the period before/after the introduction of the intraday market, respectively.

Source: authors' computations and data from the EPEX SPOT.

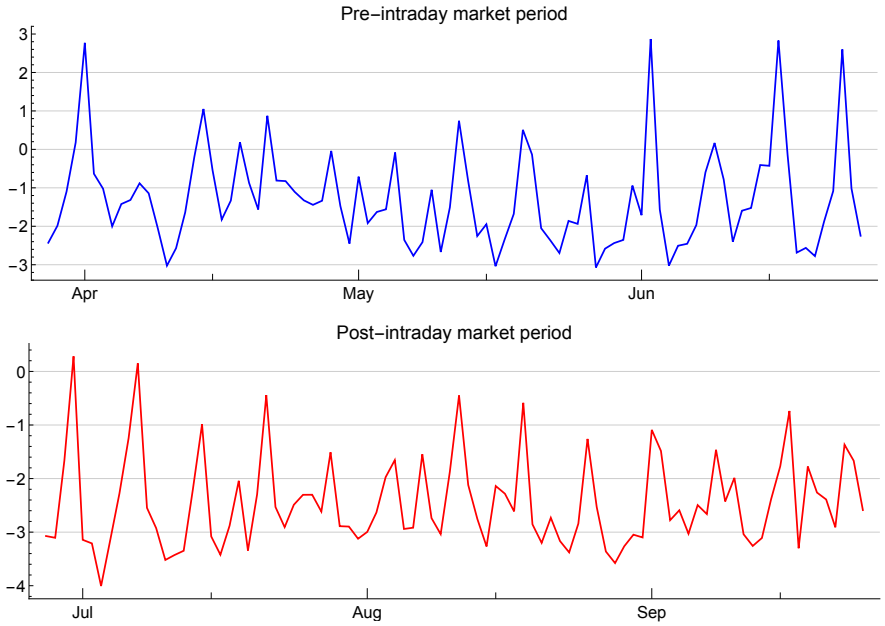
Figure A.2: Histogram of standardized daily returns for electricity prices and standard normal probability density function



The daily returns of electricity prices standardized by realized volatility (left) and by square root of realized bipower variation (right) are used to construct a normalized histogram (to model probability density function) shown in yellow bars (with bin widths determined automatically by Wolfram Mathematica software). Standard normal probability density function is shown using the blue/red line for returns before/after the intraday market introduction, respectively.

Source: authors' computations and data from the EPEX SPOT.

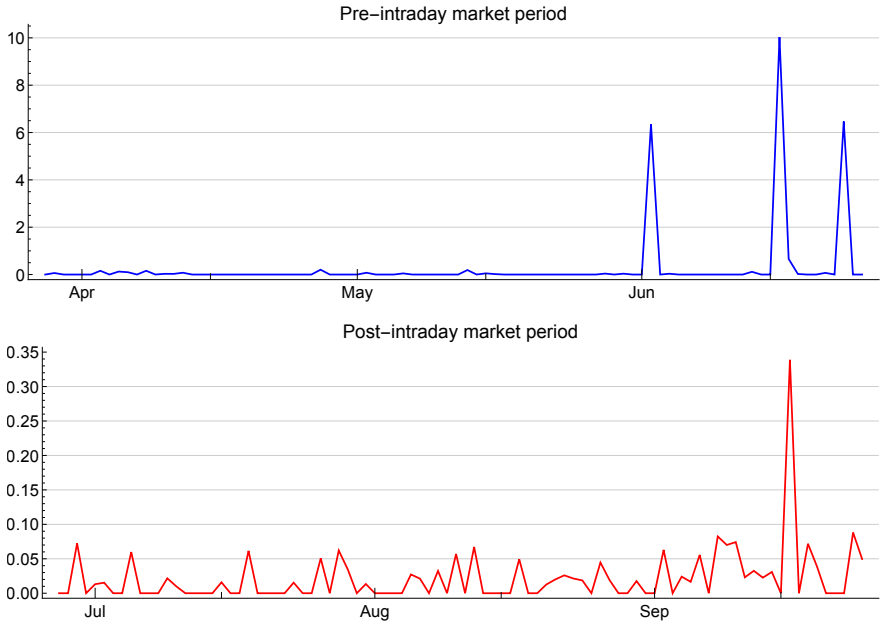
Figure A.3: Natural logarithm of RV_t for electricity prices



The figure presents graphs of $\ln RV_t$ for electricity prices. The first/second graph (blue/red) relates to the period before/after the introduction of the intraday market, respectively.

Source: authors' computations and data from the EPEX SPOT.

Figure A.4: Jump component of RV_t (90^{th} perc.) for electricity prices



This figure depicts jump components of the daily realized variance of electricity prices, RV_t, using 90^{th} percentile of the standard normal distribution for their detection. The first/second graph (blue/red) relates to the period before/after the introduction of the intraday market, respectively.

Source: authors' computations and data from the EPEX SPOT.

Appendix B

Volatility of traded volume of electricity

Table B.1: Jarque–Bera ALM goodness-of-fit test for daily electricity volume changes: 28/3/13–25/6/13 and 27/6/13–24/9/13

	Pre-intraday period		Post-intraday period	
	Statistic	p-value	Statistic	p-value
r_t	0.965	0.574	0.727	0.664
r_t/RVO_t	1.888	0.319	4.814	0.084
$r_t/\sqrt{RBV_t}$	94.631	< 0.0001	46.848	0.001

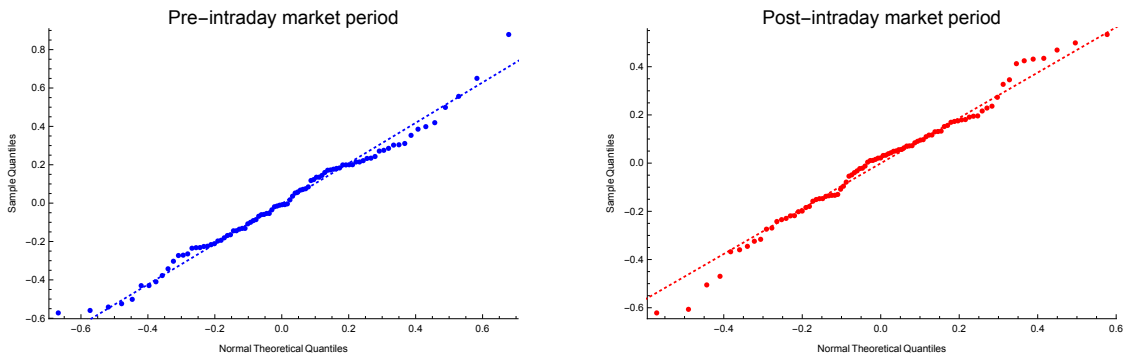
This table presents the results of the Jarque–Bera ALM goodness-of-fit test for daily electricity volume changes for both the post-intraday market period and the pre-intraday market period. The null hypothesis in this test is that the data was drawn from a normal distribution and the alternative hypothesis that it was not.

Table B.2: Cramér-von Mises goodness-of-fit test: RV_t, C_t and J_t (volume volatility)

	Pre-intraday period		Post-intraday period	
	Statistic	p-value	Statistic	p-value
RV_t	0.215	0.003	1.03	< 0.0001
C_t	0.194	0.006	0.526	< 0.0001
J_t	3.029	< 0.0001	3.494	< 0.0001

This table presents the results of the Cramér-von Mises goodness-of-fit test for RV_t, C_t and J_t for electricity volumes. The null hypothesis in this test is that series of RV_t, C_t and J_t are normally distributed and the alternative hypothesis is that that they are not.

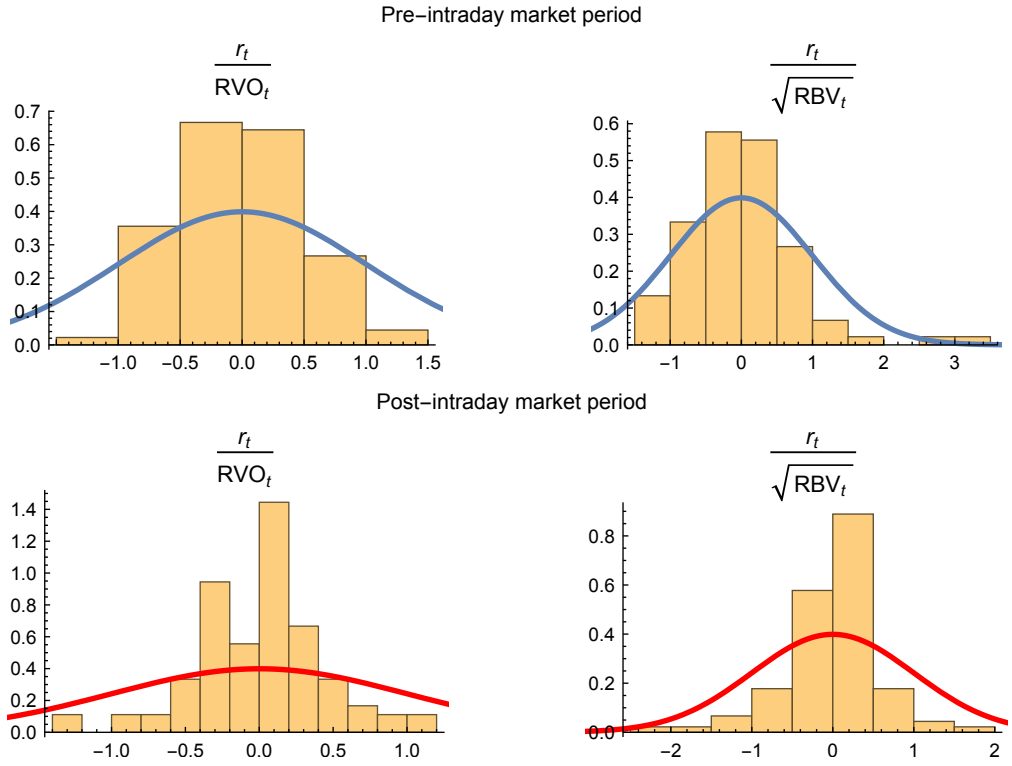
Figure B.1: Quantile-quantile plot for daily volume changes



The figure presents QQ plot of the sample quantiles of daily volume changes versus theoretical quantiles from a normal distribution with the mean and variance equal to the mean and variance of the daily returns. The graph on the left side (blue)/right side (red) relates to the period before/after the introduction of the intraday market, respectively.

Source: authors' computations and data from the EPEX SPOT.

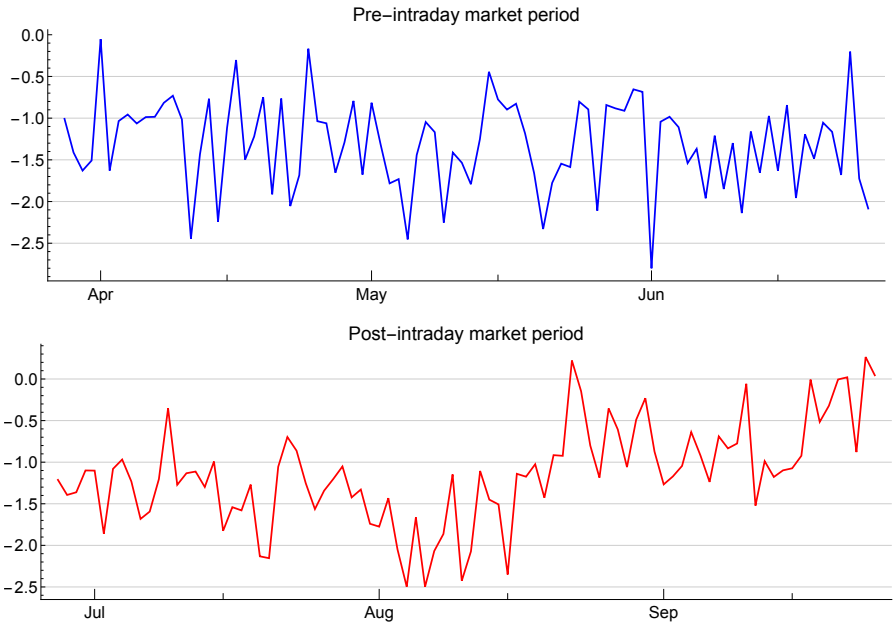
Figure B.2: Histogram of standardized daily returns for electricity volumes and standard normal probability density function



The daily returns of electricity volumes standardized by realized volatility (left) and by square root of realized bipower variation (right) are used to construct a normalized histogram (to model probability density function) shown in yellow bars (with bin widths determined automatically by Wolfram Mathematica software). Standard normal probability density function is shown using the blue/red line for returns before/after the intraday market introduction, respectively.

Source: authors' computations and data from the EPEX SPOT.

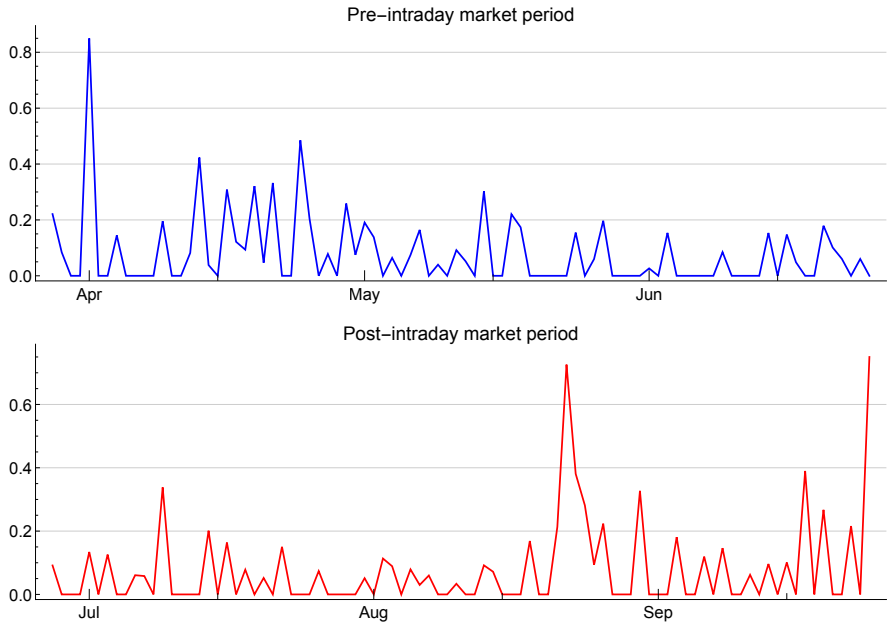
Figure B.3: Natural logarithm of RV_t for electricity volumes



The figure presents graphs of $\ln RV_t$ for electricity volumes. The graph on the left/right side (blue/red) relates to the period before/after the introduction of the intraday market, respectively.

Source: authors' computations and data from the EPEX SPOT.

Figure B.4: Jump component of RV_t (90^{th} perc.) for electricity volumes



This figure depicts jump components of the daily realized variance of electricity volumes, RV_t, using 90^{th} percentile of the standard normal distribution for their detection. The first/second graph (blue/red) relates to the period before/after the introduction of the intraday market, respectively.

Source: authors' computations and data from the EPEX SPOT.